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UNDERSTANDING THE EMERGENCE OF AGGREGATE LEVEL INNOVATION DIFFUSION THROUGH INDIVIDUAL LEVEL ADOPTION ANALYSIS

By

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ABSTRACT

UNDERSTANDING THE EMERGENCE OF AGGREGATE LEVEL INNOVATION DIFFUSION THROUGH INDIVIDUAL LEVEL ADOPTION ANALYSIS

By

Goksel Yalcinkaya

Understanding the diffusion process of new products is a key factor in business success. Firms have been able to understand the adoption of their product at the individual level (micro) and the diffusion of their product at the aggregate level (macro), but they have not been able to link the two, thus leading to difficulties of demand estimation, which in turn has led to shortages in supply or oversupply as well as challenges to developing effective marketing strategies (e.g., pricing, branding). This study proposes a model of innovation diffusion, which emerges from individual level adoption decisions, and shows how the aggregate level properties of the diffusion of innovations are in fact the results of variations at the individual level. The study investigates, both domestically and internationally, the four different dimensions of social processes and how each of these social process dimensions plays a role in individual adoption decisions. By showing the differential effects of social process dimensions on adoption decisions, the study provides a more refined understanding of the interplay among innovation characteristics, individual heterogeneity, and aggregate adoption.

DEDICATION

This dissertation is dedicated to my uncle, Prof. Nizam Aydin, who made all of this possible for his endless encouragement and patience.

And also

To my wonderful, supportive, loving fiancé, Ceyda, for always standing by me.

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CHAPTER 1

INTRODUCTION

Background

The introduction of new products provides firms increased sales, profits, and competitive positioning (Sivadas and Dwyer 2000). Given the high failure rate of innovations as well as the often large investments in innovations, accurately predicting the adoption and diffusion of an innovation as early as possible is essential for a firm to be able to plan and control its operations, avoid preventable financial loses and concentrate resources on the support of innovations that have a higher probability of success (Bayus, Hong, and Labe 1989; Goldenberg et al. 2000). Therefore, marketing managers have long been interested in how new products gain acceptance in the marketplace. This research aims to provide a better understanding of the factors that are pertinent to successful adoption of new products.

Although a considerable amount of research on the adoption and diffusion of innovations has been put forward and led us to gain substantive insights, theoretically, there are a number of limitations with the extant literature which have severely limited our understanding of the adoption and diffusion relationship. First, understanding the diffusion of new product innovations within a market has resulted in two differing streams with a central contradictory assumption, i.e., understanding the factors driving adoption (which assumes heterogeneity of markets) while simultaneously understanding diffusion at the aggregate level (which assumes homogeneity within the market) (Goldenberg et al. 2000; Goldenberg, Libai, and

Muller 2001a). At a micro-level, marketing academics and practitioners are interested in understanding the interaction between product level characteristics and individual level characteristics that drives individual adoption. This interest has resulted in a substantial literature stream characterized by micro-level approaches, which focus on differences among potential adopters and the effects of these differences on consumers' adoption decisions (e.g. Chatterjee and Eliashberg 1990; Horsky 1990; Rogers 1995). These types of models generally assume that individuals maximize some personal objective function (e.g., utility of the product) and update their beliefs as more information arrives in the market.

Alternatively, macro-level approaches (e.g. Bass 1969; Fisher and Pry 1971; Golder and Tellis 1997; Mahajan and Peterson 1978) recognize that enhanced understanding of individual adoption is not a perfect reflection of the diffusion of such product innovations through a market (a key aspect to formulating marketing strategy planning, production, pricing strategies, etc.). These macro approaches provide for estimates of market level diffusion, paying little attention to individual level adoption decisions (i.e., assuming homogeneity of the population of adopters). The divergence of underlying assumptions coming from these two approaches has resulted in theoretical inconsistencies in the literature hampering a holistic understanding of the interconnected relationship between adoption and diffusion which then, by extension, has limited the ability of marketers to effectively develop appropriate marketing strategies. To overcome this limitation, it can be argued that the best manner of understanding macro-level diffusion is to understand the aggregation of micro-level variations as the micro-level adoption decisions form, in aggregate, macro-level diffusion.

However, employing micro-level approaches to investigate macro-level diffusion brings forth a series of limitations in the literature. Most notably, there is a persistent difficulty of determining how aggregate phenomena evolve from changes in individual actions. Specifically, micro-level adoption approaches look at individuals whereas macro-level diffusion approaches look at society, the collection of individuals (Mahajan, Muller, and Bass 1990; Sultan, Farley, and Lehmann 1990). An important distinction between these two approaches is that social processes play a critical role for adoption in the latter. In this study, social processes consist of four different dimensions: personal interaction, media exposure, social pressure, and network externality. Although studies in the innovation diffusion literature emphasize the importance of social processes (e.g. Goldenberg, Libai, and Muller 2001b; Liu 2006; Mahajan, Muller, and Kerin 1984; Money, Mary, and John 1998), there is little or no insight into the relative importance of the different dimensions of social process as drivers of product innovation adoption. Given the importance of social processes, a method that takes into account its dimensions and identifies their distinct contributions seems a much needed extension to current literature. However, the full incorporation of social processes to any research is not an easy task because of the underlying complexity of the social interaction processes. The dissemination of information in a given social system is considered to be complex since it involves a large number of individuals and their interactions, which ultimately generates large-scale, collective behavior (Goldenberg et al. 2001a).

Historically, it is hard to predict the emergence of patterns when the system is complex (Waldrop 1992). Therefore, even though diffusion models often describe innovation diffusion patterns over time fairly well, it is unclear how interpersonal effects (i.e., personal interaction, social pressure) and external effects (i.e., media exposure, network externality) influence the shifting nature of the S-shaped diffusion curve[1] at the aggregate level. This is a critical theoretical shortcoming as the conceptual basis of new product diffusion within a market is actually the interaction of social actors (i.e., where one adopter influences other individuals within a market to adopt – hence diffusion occurs). Standard diffusion models capture social processes only moderately and lack how the relative importance of each social process dimension alters the shape of the diffusion curve. Yet it is often implicitly assumed that social processes are prominent factors affecting adoption decisions. It is argued in this study that the four dimensions of social processes are likely to have different relative importance for new product adoption. The differences in any one of these social processes would generate different S-shaped curves. Therefore, understanding how different elements of social processes are influential on adoption decisions may shed light on the prominence of this factor. By employing the computer-sited Agent-Based Modeling (hereafter, ABM) technique the current study simulates the diffusion process within a social system and provides an opportunity to explore how the different dimensions of social processes influence the shape of the diffusion curve at the aggregate level. This has not been fully examined in previous research due to the difficulty of gathering actual consumer data. Empirically recorded

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[1] S-shaped curve shows a cumulative percentage of adopters over time – slow at the start, more rapid as adoption increases, then leveling off until only a small percentage of laggards have not adopted. To see more information on S-shaped curve, please refer to Appendix A.

consumer behavior data on adoption decisions are sparse, and in most cases available data are based on aggregate sales (Goldenberg et al. 2001b; Mahajan and Muller 1994).

Second, the value of a new product to a consumer depends partly on the extent to which it is adopted by groups of consumers, and hence becomes a social effect. Social effects can be examined via *network externalities*- a change in the benefit that an individual derives from a product when the number of other individuals consuming the same kind of product changes (Katz and Shapiro 1986; Markus 1987). To date, past research has offered very few insights in regard to this notion's role of increasing returns to consumers that makes its effects so powerful. Furthermore, these network effects have traditionally been investigated as exogenous variables and their moderating role between innovation and individualistic characteristics and adoption decisions have not received the attention they deserved in innovation diffusion literature. As such, a key moderating role of network externalities is studied in this research. Because innovation diffusion theory has placed considerable weight on the value of network effects for faster innovation adoption and because of the widely held belief among managers that accurate estimation of innovation diffusion involves understanding the role of network effects, examining this notion is particularly important in advancing the literature.

Lastly, in an era of global business activity, understanding the cross-market applicability of the linkage between micro-level adoption and macro-level diffusion becomes increasingly important, as even firms highly successful in their domestic operations (e.g., launching products) can stumble when they expand their operations abroad. As such, success in today's increasingly competitive global markets depends on understanding decision-making processes of consumers. The effects of social process dimensions on consumers' decision-making, thus, on adoption might vary across cultures. Culture plays such an important role in here since each of these social processes' effect on adoption decisions in a given country would be expected to be different from those of another country because of cultural differences. A better understanding of consumers' decision-making processes on adoption of new products enables firms to deliberate their market expansion strategies. For example, Kellogg Inc. entered into India market in the late-1990s. Indian consumers did not pay much attention to breakfast cereals because most consumers either prepared breakfast from scratch every morning or ate only biscuits with tea. Thus, like many of its counterparts, Kellogg's expansion to India proved unsuccessful, and, after three years in the market, sales stood at an unimpressive $10 million (Arnold 2003).

Extant research indicates heterogeneous responses to new product innovations (Gatignon, Eliashberg, and Robertson 1989; Mahajan and Muller 1994; Takada and Jain 1991; Talukdar, Sudhir, and Ainslie 2002), necessitating managers understanding of country level factors that determine these variations in order to develop international strategies effectively. Toward this end, researchers have been attempting to understand the underlying forces that exert the most influence on adoption decisions (Gatignon et al. 1989; Helsen, Jedidi, and DeSarbo 1993; Takada and Jain 1991; Tellefsen and Takada 1999). For example, past literature on diffusion has indicated that unique interactions among actors of the society play a prominent role in adoption of a new product (Goldenberg et al. 2001b; Krider and Weinberg 1998; Liu

2006). Because of this need, the role of local interactions in international innovation diffusion will be examined, thus extending the international marketing literature by exploring how complex social systems generate collective behavior in different countries. As a result, a more comprehensive understanding of innovation diffusion is provided.

There are two primary purposes of this research project. First, this study will empirically test an extended version of Rogers's model (1995), linking micro-level adoption behavior to macro-level diffusion by examining the strength of the social processes. Secondly, this study will test the sensitivity of S-shaped diffusion curves over different levels of social process dimensions. Based on these two purposes, the following research questions will be investigated:

- Can social processes help to advance our understanding of the relationship between micro-level adoption decisions and macro-level diffusion of innovations?
- To what extent do changes in individual characteristics as well as product innovation characteristics account for changes in the shape of the diffusion curve over time?
- How does the speed at which innovations get adopted and diffused through the market vary with different types of social processes?
- If macro-level diffusion of innovation drivers are in fact the result of actions at the micro-level, is this claim also applicable internationally?

The remainder of this study is organized as follows. The next section gives a brief history of the diffusion of innovation models and discusses theoretical issues concerning the diffusion of innovations. After the review and discussion, the two major bodies of research of diffusion models are compared. Next, the model for understanding diffusion of product innovations as a function of individual level adoption decisions is introduced and the major components are discussed. Then, the methodology employed in this study is described along with the presentation of analysis and results. The article concludes with contributions for theory and implications for management.

CHAPTER 2

THEORETICAL DEVELOPMENT

1. The Theory of Innovation Diffusion

Innovation refers to an idea, practice or object perceived as new by an individual or other unit of adoption (Rogers 1995). For example, Microsoft's introduction of wireless and online gaming in the Xbox 360 in 2005 was seen as setting new standards in gaming hardware. Diffusion refers to "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers 1995, p. 5). As such, the Xbox 360's adoption by consumers in 2005 began the product's diffusion through the marketplace. Theoretically, innovation diffusion theory, that describes the patterns of adoption, explains the mechanisms by which an innovation occurs, and assists in predicting whether it will be successful was formalized by Rogers in his 1962 book titled Diffusion of Innovations.

Innovation diffusion theory is actually a theory of communication regarding how information is dispersed within a social system over time (Rogers 1995). Because people place different emphases on how much they rely on media and interpersonal communication for new ideas and information, they adopt new products either earlier or later in a product's lifecycle. The consumer product adoption process based on relative adoption time categorizes individuals as innovators, early adopters, early majority, late majority, and laggards.

At the most general, two broad classes inform innovation diffusion research: macro-level (aggregate) models and micro-level (individual) models. Macro models examine the market in aggregate and assume homogeneity in the population of adopters, whereas micro models specifically focus on individual adoption behavior and assume that the product adoption rate of each individual is different and idiosyncratic. The Rogers's model is considered to be example of the former while the Bass model is included in the latter category. It is interesting to note that the while the literature encompassing macro models is plentiful, less has been done with respect to the development of micro models. The following section discusses the different types of models and reviews several notable examples from the literature. The research described here mainly relates to marketing applications.

1.1. Micro-Level Models

Micro-level models of adoption of innovations argue that there are differences among individuals in terms of how innovative they are in their tendencies to adopt new innovations, and which types of information about a new product are most persuasive prior to adoption. When a new product is introduced, there exists uncertainty in the minds of potential adopters regarding how superior the new product is versus existing alternatives (Hall and Khan 2003). Individuals attempt to reduce this uncertainty by acquiring information about the new product. More innovative individuals tend to acquire such information via media and other external outlets such as expos, trade shows, specialized magazines, experiments, etc. For instance, exhibitions (i.e., major trade shows and expos) play a key role for innovative people to adopt as these exhibitions provide a convenient, cost-effective way to gather the information required to make sound purchasing decisions (Aggarwal 1997; Barczak, Bello, and Wallace 1992). Likewise, innovative individuals read many more specialized magazines about new products and innovations than the average individuals (Rogers 2003). More imitative individuals tend to acquire such information from interpersonal channels such as word-of-mouth communication and observation (Mahajan et al. 1990; Rogers 1995). In these models, modeling extends to mathematical representations of individual decision processes and allows agents to display heterogeneity of belief and preferences (Gatignon et al. 1989; Robertson and Gatignon 1986). Although individuals have perfect knowledge of the price of an innovation, they can only learn about its quality or reliability through the experience of those who have already purchased (Krider and Weinberg 1998; Liu 2006; Mahajan et al. 1984).

Rogers has developed one of the better-known theoretical approaches to diffusion of innovation. Rogers (1995) stated that adopters of any new innovation or idea could be categorized as innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%) and laggards (16%), based on a bell curve (Appendix B). Each adopter's willingness and ability to adopt an innovation would depend on their awareness, interest, evaluation, trial, and adoption. Rogers theorized that innovations would spread through society in an S-curve (implies that new product sales are initially slow, then sales grow at a rapid rate, then the rate of growth tapers off, and finally declines with time), as the early adopters select the technology first, followed by the majority, until a technology or innovation is common. Some individuals are very innovative and are the first to try new products, whereas others are less so, and typically wait until many of their neighbors, etc. have already bought the new product before they do the same. The speed of adoption of a new product has been shown to be a function of several factors including relative advantage, compatibility, complexity, observability, and trialability.

Within the field of marketing, due to the underlying complexity coming from personal interactions, which typically involves a large body of consumers interacting with one another, a relatively limited number of published studies have examined individual differences in consumers' preferences. Of these, Roberts and Urban (1988) develop a brand choice model which accounts for consumer heterogeneity, specifically with respect to product attribute preferences as well as uncertainty, risk, and interpersonal communication. They employ a decision-analytic framework in which consumers maximize their risk adjusted expected utility. Consumers' beliefs change and are updated as a result of word-of-mouth communication. Kim, Srivastava and Han (2001) propose a multi-generation adoption model that incorporates technological substitution and repeat purchase behavior. In their model, consumers differ in their purchase history, expectations of future generations of the product, and current preferences. Sinha and Chandrashekaran (1992) take a different approach by developing a model that allows for consumer heterogeneity with respect to timing as well as the probability of adoption.

Oren and Schwartz (1988) investigate the selection between an innovative product with uncertain performance and a currently available product with certain performance where uncertainty leads risk-averse consumers to delay adoption until they get more evidence on the performance. Early adopters are those who are less averse to risk while later adopters are imitators who delay purchase until they get enough information from the market to overcome their initial uncertainty. In a similar vein, Chatterjee and Eliashberg (1990) develop a model where adopters are risk averse and adopt a product only if their expectations of its performance exceed a 'risk hurdle' and a 'price hurdle'. The adopters update their expectations of performance based on the information (positive or negative) they receive. Adopters are hence heterogeneous in the cumulative information they need for adoption. The authors derive a diffusion curve by aggregating the predicted individual adoption behavior over the population.

Horsky (1990) also develops a model based on individual level utility maximizing behavior to explore why and when new products are purchased. He demonstrates that a utility maximizing individual will have a reservation price for the product which is a function of the product benefits and his wage rate. By assuming that the wage rate has an extreme value distribution across the population, he is able to derive, for the aggregate process, an income-price dependent logistic adoption equation. It is important realize that the structure of consumer heterogeneity does not play a role in determining adoption timing in this model. The distribution of consumer heterogeneity in wages affects only the market size.

The model developed by Song and Chintagunta (2003) incorporates both heterogeneity and forward looking behavior by consumers in the adoption of new high-tech durables products. In their model, consumers have expectations of the future states of prices and quality levels, both of which change over time leading to a probability distribution on the transition of future states of these variables conditional on current states. A consumer can choose to either adopt or not adopt a product in each period and chooses the alternative that maximizes the discounted sum of expected utility. The authors aggregate these individual level adoption decisions to obtain an aggregate diffusion curve, and use the more easily available aggregate level data to estimate the individual level decision parameters.

Although micro-level adoption models provide a theoretical basis for the new product adoption phenomenon and addresses the unrealistic assumption of population homogeneity assumed by the macro-level diffusion studies, these studies do not exploit the structure of consumer heterogeneity in order to assist managerial decision making. Key shortcomings are as follow. First, the micro-level studies assume heterogeneity of potential adopters' internal characteristics (such as individual preferences, choices, etc.), while neglecting the heterogeneity caused by the social network to which potential adopters are linked. Second, the micro level perspective does not model aggregated adoption behavior very well. In order to ensure aggregability, the models of individual decision typically rely on strong assumptions about the degree of economic rationality displayed, for example that all agents have the same model of the environment and differ only in their beliefs about parameter values. Finally, these models take into consideration differences in consumer attitudes and preferences. Many parameters are necessary to adequately describe individual behavior. Such models are therefore less parsimonious.

1.2. Macro-Level Models

Macro-level diffusion models attempt to understand the diffusion processes across populations (e.g., firms, countries) and assume homogeneity in the population of adopters. Specifically, the major emphasis has been on finding the adoption patterns and incorporating marketing mix variables, such as price and advertising. Although there have been attempts to reduce the homogeneity assumption by looking at different consumer segments (e.g., Lee, Kwon, and Schumann 2005), these types of models have generally addressed the market in aggregate, paying little attention to individual level adoption decisions.

The Bass model (which tries to estimate how many individuals will buy a new product as the new product gains more acceptances over time) represents one of the early attempts at developing a macro-level diffusion model. The Bass model follows Rogers's innovation diffusion theory, which emphasizes the role of communication efforts, whether those efforts are external in nature, (e.g., mass advertising) or more informal in nature, (e.g., word-of-mouth communication or observation and imitation) as driving the product adoption pattern. The model captures both the innovative and imitative aspects of product adoption. The Bass model denotes the innovative characteristic with its coefficient, p, and the imitative characteristic with its coefficient, q. The coefficient of innovation (i.e., p) captures the relative importance of innovative individuals in generating sales for the new product. The coefficient of imitation (i.e., q) captures the relative importance of imitative individuals in generating sales for the new product. The model operates such that, regardless of the values of p and q, as more and more individuals adopt or buy the new product, the relative impact of imitative individual purchases takes on greater importance in determining the sales curve. The S-curve that is then produced represents cumulative sales to date. The model assumes that there are differences among individuals in terms of how innovative they are in their tendencies to adopt new products, and which types of information about a new product are most persuasive prior to adoption.

The Bass model has become widely accepted in the innovation diffusion research because of its parsimony and explanatory power (Roberts and Lattin 2000). However, the model has its own limitations. A fundamental weakness of the Bass model is to assume all consumers to be homogeneous (Tanny and Derzko 1988). It does not specify at the micro level what is the consumer decision-making during time and how consumers communicate and influence each other. Homogeneity in here implies that at any point in the process, all individuals who are yet to adopt have the same probability of adopting in a given time period. The direct implication of this assumption is that differences in individual adoption times are purely hypothetical. Such an implication clearly contradicts the notion that markets are fundamentally heterogeneous. In addition, the model does not include the effects of marketing efforts, such as advertising and price. This is a serious problem because most managers want to influence sales with these two variables. Another limitation is that the model does not take into account potential external effects, such as competition. Knowing the competition organization faces is important for managers since competition may increase the entire market potential due to increased promotion or product variety. In addition, a newly offered brand could compete for the same market potential and hence slow down the diffusion of the existing brands.

2. Extensions of the Bass Model

From its introduction to the present, various extensions of the Bass model have been developed. One popular approach has been to incorporate the effects of marketing mix variables. As an example, Horsky and Simon (1983) investigate the effects of advertising on the diffusion of new products. The authors indicate that advertising informs the innovators of the product, who in turn influence the imitators. Simon and Sebastian (1987) also examine the influence of advertising, specifically focusing on its effects on either the innovation or imitation components of diffusion. In their study, Kamakura and Balasubramanian (1988) look at how price affects the market potential or adoption probability of the product. Their results indicate that price affects the diffusion process only for relatively high-priced goods.

While incorporating marketing mix variables into the basic Bass model has been a prevalent research direction, other avenues have been explored as well. For example, Mahajan and Peterson (1978) model the market potential as a function of time-varying exogenous and endogenous factors such as socio-economic conditions, population changes, and government or marketing actions. Jain, Mahajan, and Muller (1991) take a somewhat different approach in their extension of the Bass model by noting that previous research has primarily focused on the demand side of what is a supply-demand issue, by examining the diffusion in the presence of supply restrictions.

Other contributions to the diffusion literature include the international diffusion of new products. For example, Heeler and Hustad (1980) provided one of the early international diffusion analyses in the marketing literature. Their study investigated how the basic parameters varied by country and found that a degree of forecasting error with international data was higher when it was compared to U.S. data. Later, Gatignon, Eliashberg, and Robertson (1989) attempt to explain the differences in diffusion patterns across countries. The study, focusing exclusively on consumer durable goods, has shown that the diffusion of a new product is a culture-specific phenomenon and that the differences in the diffusion patterns across countries can be explained by certain country-specific factors. Takada and Jain (1991) took a different approach and observe that when an innovation is introduced first in one country and with a time lag in subsequent countries, the diffusion rate in the subsequent countries is faster than the rate in the first-introduced country. Their findings suggest that lag time has a positive effect on the diffusion rate in the lag countries. Dekimpe, Parker, and Sarvary (2000) examine the sequential adoption of a technological innovation by various countries. Furthermore, Talukdar, Sudhir, and Ainslie (2002) explore the diffusion of multiple products across a number of different countries. These researchers investigated the impact of a number of covariates on the Bass model parameters.

Some authors have extended the single product diffusion models to examine successive generations of an innovation. Building upon the Bass model, the model developed by Norton and Bass (1987) demonstrates the diffusion of successive generations of a technological innovation. They illustrate how a new generation of an innovation will replace sales of the previous generation product, dramatically altering the characteristic S-shaped curve. Similarly, Mahajan and Muller (1996) propose an extension to the Bass model that captures diffusion as well as substitution of successive generations of a technological innovation. Their model additionally accounts for the effects of partial "leapfrogging" and partial cannibalization. A practical benefit of their model is that it guides one in determining optimal introduction times of new generations of the product. More recently, Danaher, Hardie, and Putsis (2001) incorporate a proportional hazards framework to model successive generations of a technological innovation that additionally captures the impact of marketing mix variables. They empirically evaluate their model by examining the effect of price on the sales of two generations of cellular telephones.

The traditional method of forecasting innovation diffusion in macro level studies is to fit one of a standard set of mathematical functions to aggregate adoption data gathered using surveys (Mahajan and Peterson 1978). This approach suffers from a number of obvious disadvantages. First, data collection in this way is potentially unreliable and studying only substantially adopted innovations introduces an obvious selection bias. Second, the estimation of non-linear systems is much more difficult and their statistical properties are less well known. Third, it has been argued that macro level diffusion models cannot serve as an effective predictive tool for the early years of product's life cycles (Kohli, Lehmann, and Pae 1999; Mahajan et al. 1990) since a stable estimation of diffusion parameters requires sales data from introduction through peak sales (Srinivasan and Mason 1986).

Although the lack of heterogeneity among adopters is an important shortcoming of the macro approach, there are several advantages that the macro perspective can offer. First, the macro perspective provides a parsimoniously analytical way to understand the whole market and interpret its behavior. Second, the managers would like to have market level insights about the adoption behavior to work with. Finally, it is relatively easy to get market level data such as average price and number of adoptions in a given year.

3. Social Processes and Diffusion

The fundamental idea underlying the concept of diffusion is that interactions between individuals are the driving force behind the evolution of behavior, beliefs and representations (Rogers and Kincaid 1981; Valente 1995). Interactions may be direct (i.e., from one individual to another) or indirect (i.e., transmitted through a medium or institution such as press and publicity, political parties and trade unions, markets, etc.). Both types usually operate in tandem and their effects are combined. Indirect interactions generate complex dynamics in which the social structure plays a decisive role, to the extent that it conditions the propagation of inter-individual influence.

Investigating the patterns of innovation diffusion through social networks has gained some attention lately (Abrahamson and Rosenkopf 1997; Goldenberg et al. 2000; Weisbuch 2000). These models are similar in some respects to models of contagion, in that they attempt to estimate how many individuals will buy a new product as the new product gains more acceptance over time (Moore and Newman

2000). However, while these models elucidate social factors as the drivers of new product diffusion, they neglect to elaborate that each of these factors may affect diffusion in a particular way. Hence, the study proposes a diffusion model that explicitly includes consumer decision-making affected by four different types of social processes: media exposure, personal interaction (word-of-mouth), social influence, and network externality. In fact the agents of this simulation model both decide according to their preference and are influenced by other agents' decisions according to threshold rules (Granovetter 1978). The model allows us to study the diffusion patterns over time for different levels of influence as well as types of social processes. In particular, the focus is on four different dimensions of social processes that differ in weight, the strength of the social processes on potential adopters, and the heterogeneity of the consumers.

3.1. Personal Interaction and Social Pressure

Both personal interaction and social pressure occur when communication among individuals exists. Therefore, these two social processes are grouped under *interpersonal effects* in this study. *Personal interaction* is defined as the spreading of information about products through human interaction (Westbrook 1987). Innovation diffusion theory suggests that potential adopters of an innovation are influenced by personal interaction or word-of-mouth. The significant role of personal interaction in the dissemination of product information is supported by broad agreement among academics (Arndt 1967; Bass 1969; Mahajan et al. 1990; Sultan et al. 1990). Individuals tend to trust word-of-mouth communication with a reference group more than they do external communication channels such as media in estimation of brand alternatives (Hartline and Jones 1996; Herr, Kardes, and Kim 1991; Parasuraman, Zeithaml, and Berry 1988; Rio, Rodolfo, and Victor 2001), frequently respecting word-of-mouth as a means to reduce risk in making purchase decisions.

Although marketing efforts such as advertising and promotion are important at early stages of the adoption process, personal interaction among prior or potential adopters becomes far more critical as time passes (Bass 1969; Rogers 1995). When an idea is perceived as new, individuals often seek information to evaluate its expected utility and consequences (Goldenberg et al. 2001a). Despite the fact that marketing efforts are a cost effective way to create awareness of a new product, personal interaction is perceived as a more credible source of information (Herr et al. 1991; Rogers 1995), thus, having more impact on a potential adopter's willingness to adopt. While marketing efforts have a greater impact on innovative individuals[2], the effects of personal interaction have a greater impact on the much larger number of imitative individuals (Rogers 2003). Hence, personal interaction is associated more with q, the coefficient of imitation.

Past research also shows that the community in which the individual operates affects her/his adoption decision (Frambach and Schillewaert 2002). For example, a member of a community can exert social pressure on other members of the community to coordinate efforts or increase the efficiency (Valente 1995). In this

[2] Rogers' research indicates that the spread of a new technology depends mainly on two factors: innovation or imitation. Innovators are driven by their desire to try new technologies or methods and the likelihood of an innovator using a new technology does not depend on the number of other users. On the other hand, imitators are primarily influenced by the behavior of their peers. The likelihood of an imitator embracing a new technology, or new way of doing work, is dependent on the number of people who are already using it.

study, *social pressure* is defined as an individual's perceptions of normatively appropriate behavior with regard to the use of new products or technologies (Valente 1995). When admired peers have adopted an innovation, an individual also feels pressure to adopt because they may experience some discomfort from other group members (whether economic or social) (Davis, Bagozzi, and Warshaw 1989; DiMaggio and Powell 1983). In addition, in most cases, individuals tend to avoid conflict within social groups (Moscovici 1985). Not using a certain innovation that everyone else uses may create some tension against individuals who resist adopting that innovation. Moreover, when peers within the social group adopt the innovation, the uncertainty associated with that innovation decreases for the others and they tend to adopt more easily. When faced with social pressures, even imitative individuals might move their adoption decisions to an earlier date. Such behavior should result in a higher coefficient of innovation (i.e., *p*) since social pressure affects potential adopters directly.

3.2. Media Exposure and Network Externalities

In order to better understand the adoption process, one should also consider the *external effects*, the effects that exist independently of individuals. Under external effects, the study examines media exposure and network externality and their influences on adoption decisions. *Media exposure* is defined as any opportunity for a reader, viewer, or listener to see and/or hear an advertising message about a new product in a particular media vehicle. A primary effect of media exposure is the dissemination of information about innovations directly to potential adopters, the media thereby acting as a major channel of communication in the diffusion process (Rogers 1995; Rogers and Shoemaker 1971). The media exposure's most powerful effect on diffusion is that it spreads knowledge of innovations to a large audience rapidly (Rogers 1995). It can even lead to changes in weakly-held attitudes. When products like PCs, telephones and televisions are first launched, demand is restricted to the most affluent consumers and to consumers in managerial and professional occupations. The wealthy and affluent individuals, in other words, tend to act as the innovators in society, are more influenced by marketing efforts such as advertising (Rogers 1995). The adoption of new products is restricted to innovators at the early stages of diffusion process because the newly offered product carries uncertainty. Because of this uncertainty, the majority of potential adopters look to other means of communication to reduce risk associated with uncertainty. Hence, media exposure is important at early stages of the adoption process and associated with p, the coefficient of innovation.

In addition, the value of innovations to the consumer depends partly on the extent to which it is adopted by other individuals- a notion that is known as network effects or externalities. Network externalities are defined as changes in the benefit, or surplus, that an individual derives from a product when the number of individuals consuming the same kind of product changes (Katz and Shapiro 1986; Markus 1987). A technology has a network effect when the value of the technology to a user increases with the number of total users in the network. The principal message of the economic literature on network effects is that consumers receive benefits from other consumers' selection of the same technology. These benefits arise from the fact that adoption of a product by a greater number of people increases the probability that this particular technology will survive and that goods compatible with it will continue to be produced (Kraut et al. 1999). For instance, Saloner and Shepard (1995) examine the adoption of ATM machines by banks. Initially, their assumption was the consumers prefer a larger network of ATM machines to a smaller one. The authors found that banks with more branches adopt an ATM network sooner and argue that this confirms that a higher network value leads to earlier adoption of a new technology, other things being equal. Given that even innovative individuals might delay adoption of an innovation until the uncertainty associated with what standard or technology will dominate among competing technologies is settled, thus, behaving like imitators, it is logical to assume that network externalities have a greater impact on q (i.e., imitative individuals) (e.g. Van den Bulte and Stremersch 2004).

CHAPTER 3

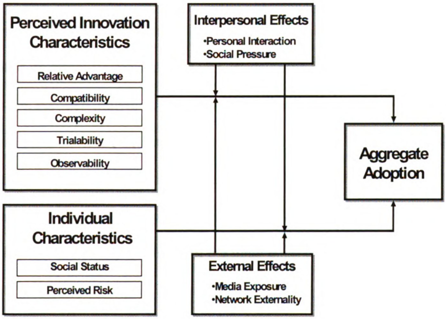
HYPOTHESES DEVELOPMENT

1. A Conceptual Framework

Based on studies on micro-level adoption and macro-level diffusion in different disciplines, we can identify different factors of innovation that have been found to influence the adoption process. Rogers (1995) identifies five analytic categories of attributes that influence the potential adopters of an innovation. The facilitators of the adoption decision are relative advantage, complexity, compatibility, observability, and trialability. Relative advantages represent the extent to which innovations are viewed as superior to the ideas they supplant. Compatibility requires that they be consistent with potential adopters' requirements, prior experiences, and values. Complexity is determined by the degree to which innovations require adopters to develop new skills and understandings. When they can be tested on a restricted basis, they score high in the category of trialability, and the visibility of their use and its effects determines their observability (Rogers 1995).

Although, it is not believed that the adoption process is only limited to these perceived attributes (e.g., Abrahamson and Rosenkopf 1997; Deffuant, Huet, and Amblard 2005; Sultan and Chan 2000), these elements would be helpful in formulating questions for potential adopters to better understand which factors make adoption possible or desirable. Understanding the way in which the adoption process unfolds, simply identifying features that determine its ultimate success or failure, requires a larger framework which investigates complicated interactions among multiple agents. Therefore, in addition to the attributes listed above, which influence the adoption decisions at the individual level, we indicate a variety of external or social conditions as well as individual characteristics that accelerate or slow the adoption process. With the inclusion of external, social, and individual elements, a more robust model is provided to better explain innovation diffusion so that marketing managers can execute appropriate strategies for predicting demand. The conceptual model is depicted in Figure 1.

Figure 1: A Conceptual Framework of Aggregate Adoption.



2. Innovation Characteristics and Aggregate Adoption

Individuals' perceptions of an innovation affect their evaluation of adoption of a new product (e.g., Rogers 1995; Tornatzky and Klein 1982). Rogers (1995), through a synthesis of several previous studies examining adoption behaviors, identified several attributes of an innovation that are key influences on acceptance behavior. According to Rogers, these characteristics, as stated previously, include relative advantage, complexity, compatibility, trialability, and observability.

Although Rogers introduces the innovation characteristics that influence individuals' adoption decisions, the Bass model takes examination at the aggregate level and provides a foundation for the development of diffusion models. Considerable research across many disciplines including marketing, agriculture, sociology, and anthropology, suggests that most successful innovations have an S-shaped rate of adoption, although the slope of the curve varies (Rogers 2003). The Bass model adjusts the slope of the S-shaped curve according to two main parameters: p and q, the coefficient of innovation (external influences) and the coefficient of imitation (internal influences). Because the internal influence relies on the interaction between individuals who have already adopted the innovation and potential adopters while the external influence affects potential adopters directly (Ho, Savin, and Terwiesch 2002), relative advantage and observability attributes of the innovation will have a greater impact on imitator individuals whereas complexity, compatibility and trialability attributes of the innovation will have a greater influence on innovator individuals (Rogers 2003).

2.1. Innovation Characteristics and Internal Influences

Among all five innovation characteristics, relative advantage and observability can be theorized to be associated with q (i.e., internal influences) since potential adopters rely more on the opinions of others who adopted the innovation than external sources such as the media. By interacting with other individuals, potential adopters learn more about the innovation's benefits and lessen uncertainty; ultimately, reducing the risk associated with the innovation. Given that when new products are first introduced to the market they carry clear uncertainty, observability attribute of the innovation plays an important role on adoption decisions as well since observability gives a chance to potential adopters to see how the innovation carries out in the marketplace.

Research indicates that the *relative advantage* (benefit) of an innovation is one of the most important predictors of the adoption decision (Moore and Benbasat 1991; Robinson 1990; Tornatzky and Klein 1982). Rogers (1995) defined relative advantage as "the degree to which an innovation is perceived as being better than the idea it supersedes" (p. 15). Based on this definition, the most important determinant of the advantage derived from adopting a new product is the amount of improvement which the new product offers over any previous ones. More specifically, most of the time, it is not absolute supremacy of a new alternative that actualizes the adoption decision, rather it is the extent to which it improves on the existing options (Hall and Khan 2003).

When comparing products and services, individuals may consider not only economic gains but also other variables such as reduction in risk, decrease in discomfort, saving in time and effort, and immediacy of rewards (Rogers 1995). For example, Holak and Lehmann (1990) note that if substantial advantages are associated with a new product, perceived purchase risk may be lessened as the potential adopter overlooks its shortcomings. Similarly, Hall and Khan (2003) argue that although the most obvious benefits may seem to be increased utility from the new good, it may also include such non-economic benefits as the enjoyment of being first to use the new product, which may generate added prestige to the individual. Thus, if an individual perceives that the outcome resulting from the adoption of the innovation will result in a positive value (e.g., improved job performance, time saving, increased prestige, and reduced cost), the intention toward the adoption itself is likely to be more positive because of these additional benefits gained (Davis et al. 1989).

Similar to relative advantage, the observability characteristic of an innovation also plays a key role for individuals' adoption decisions. Rogers (1995, p.16) defined *observability as* "the degree to which the results of an innovation are visible to others". Underlying the relationship between observability and adoption is the belief that observability allows an individual to see how an innovation works out for others and hear about the experiences of an innovation from others. Observability also speaks directly to the level of uncertainty faced by the potential adopter (Moore and Benbasat 1991; Rogers 1995). Individuals that are considered to be risk averse (e.g., late adopters) adopt new products when they have more information and greater exposure to the product. Given that when new products are first introduced to the market they carry uncertainty, the observability attribute of the innovation plays an imperative role to reduce uncertainty as the observability attribute of an innovation gives potential adopters a chance to see how the innovation carries out in the marketplace. By interacting with the other individuals, potential adopters learn more about the innovation's specific advantages as well as its risks through others' observations. This, in turn, lessens uncertainty, ultimately reducing the risk associated with the innovation. Because personal interaction plays a more important role than the media, observability is associated with the *q* (i.e., internal influences) parameter of the Bass model.

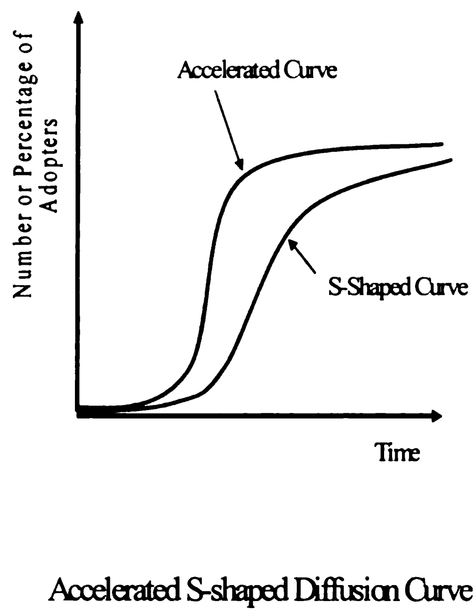
In sum, the speed of adoption of a new product has been shown to be a function of several factors including the product's relative advantage over existing products and the degree to which the benefits of the product are observable (Rogers 1995; Rogers 2003). To the extent that a new product possesses each of these attributes, its likelihood of success in the market is improved. However, for many potential adopters, it is hard to perceive how superior the new product is versus existing alternatives when a new product is introduced. Thus, uncertainty about the product exists. To reduce this uncertainty, potential adopters try to acquire information about the product via interpersonal channels (internal influences) such as word-of-mouth communication and observation (Hall and Khan 2003). Therefore, as the level of interactions among individuals intensifies (a higher value of q), potential adopters will obtain more information about the product and better able to see the benefits of the product. This in turn lessens the uncertainty associated with the innovation and quickens the adoption of the innovation. Therefore, the following is hypothesized:

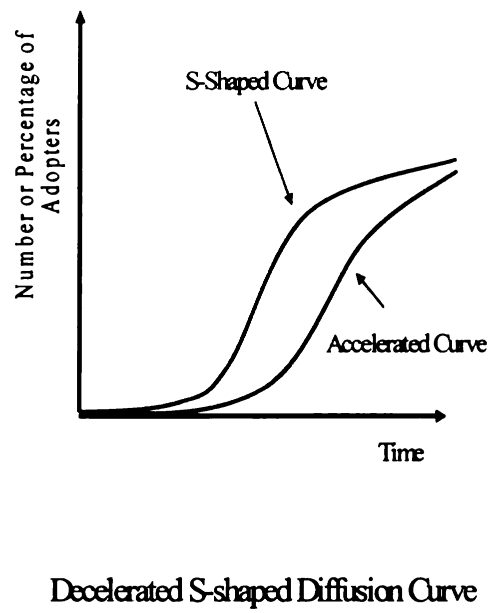
H_{1a}: *Relative advantage has a stronger positive effect on aggregate adoption when personal interaction and network externatilities are more pronounced than media exposure and social pressure; this will result in an accelerated*[3] *S-shaped diffusion curve.*

[3] Accelerated means an earlier new product takeoff related to start will occur and the slope of the S-shaped diffusion curve will be steeper. See Figure 2.

H_{1b}: *Observability has a stronger positive effect on aggregate adoption when personal interaction and network externatilities are more pronounced than media exposure and social pressure; this will result in an accelerated S-shaped diffusion curve.*

Figure 2: Accelerated and Decelerated S-shaped Diffusion Curves





2.2. Innovation Characteristics and External Influences

Because the external influences such as media exposure affect potential adopters directly (Ho et al. 2002; Van den Bulte and Stremersch 2004), compatibility, complexity, and trialability characteristics of new products are associated with p, the coefficient of innovation. Rogers (1995) stated that "compatibility is the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (p. 15). Intuitively, if an innovation is judged to be in keeping with an individual's past experiences, values and life-style, the individual probably would be familiar with previous items and thus more capable of judging the present innovation in terms of its superiority over prior offerings. If an innovation were perceived to be incompatible with an individual's life-style, chances are that some benefits of the innovation would not be recognized by the adopter (Holak and Lehmann 1990; Rogers 1995). An innovation that has resonance with an individual, where the individual feels comfortable or familiar with the innovation, will have a greater likelihood of adoption than an innovation which lacks these attributes as a higher familiarity will cause uncertainty about the innovation to be decreased. In turn, perceived risk associated with adoption will be reduced causing the rate of adoption of the innovation to increase. (Davis et al. 1989; Rogers 1995).

Previous research has also argued that when an innovation is recognized to be compatible with an individual's existing practices she/he is likely to perceive the advantages of the innovation, as significant incompatibility requires major adjustments in practices that often necessitate considerable learning (Cooper and Zmud 1990; Rogers 2003). Similarly, if the innovation is compatible with existing knowledge, the expected costs and time involved in its use will be lower, leading to greater technological advantages to individuals, which ultimately triggers a higher rate of adoption (Cooper and Zmud 1990; Rogers 1995; Taylor and Todd 1995; Tornatzky and Klein 1982).

The degree of a new product's complexity is another important characteristic for the adoption decision. Rogers (1995, p. 15) defines complexity as "the degree to which an innovation is perceived as relatively difficult to understand and use". If an innovation is viewed as complex, it will not be perceived as being easy to try and its benefits will not easily be recognized and explained to others (Davis et al. 1989; Rogers 1995; Tornatzky and Klein 1982). Similarly, when an innovation is perceived as difficult to understand, learn and use, perceived risk associated with its usage will be higher since it requires greater effort on the part of adopters to educate themselves, which ultimately creates a need for complementary investment and increased cost (Thompson, Higgins, and Howell 1991).

According to Rogers (1995, p. 16), whether an innovation can be tried is also a key attribute for adoption. He defines trialability as "the degree to which an innovation may be experimented with on a limited basis". Rogers (1995) has recognized that trial is one of the ways of reducing uncertainty related to innovations. Ram and Sheth (1989) agree with the finding that uncertainty has an effect on individuals' adoption decisions and argue that to some extent all innovations represent uncertainty, which can lead to consumers postponing the adoption of the innovation until they can try it. The opportunity to try an adoption is an effective mechanism for reducing risk and thus might be expected to have a positive impact on the adoption decision.

Because individuals have different knowledge and skills with respect to a specific innovation and perceive different levels of complexity in its use, they value mass media more than personal interactions in terms of gaining useful insights about the innovation. The same logic is held for the compatibility characteristic since every individual's past experience, values and life-style differs from each other. Different people will have different compatibility tolerance levels with respect to an innovation. It is also true that the need for a product trial before purchase may not be the same as individuals display different past experiences. Since individuals are more likely to seek independent confirmation of the attractiveness of an innovation in these cases, they would be more hesitant to use word-of-mouth sources to make independent judgments about new products and they will be more affected by direct communication channels, which imply high external influence (i.e., p). This leads to the following hypotheses:

H_{2a}: *Compatibility has a stronger positive effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externalities; this will result in an accelerated S-shaped diffusion curve.*

H_{2b}: *Complexity has a stronger negative effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externalities; this will result in a decelerated[4] S-shaped diffusion curve.*

H_{2c}: *Trialability has a stronger positive effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externalities; this will result in an accelerated S-shaped diffusion curve.*

3. Individual Characteristics and Aggregate Adoption

Although the perceived characteristics of innovations play a very important role for innovation adoption, the role of individual characteristics on innovation adoption is equally important. Individual characteristics can lead to different individual perceptions about a particular innovation and subsequent outcomes

[4] Decelerated means a later new product takeoff related to start will occur later and the slope of the S-shaped diffusion curve will be less steep. See Figure 2.

associated with using the innovation (Speier and Venkatesh 2002; Sultan and Chan 2000). While much of the innovation diffusion literature has concentrated on finding the effects of product innovation characteristics on the adoption decisions of potential adopters, the literature has paid little attention to how individual characteristics play a role in adoption decisions (Wejnert 2002). Two sets of individual variables appear to influence the adoption of innovations: 1) social status and 2) perceived risk.

Social status of individuals refers to the relative prominence of an individual's position within a population of individuals (Wejnert 2002). Research suggests that the influence of social status on adoption decisions cannot be ignored since people holding a higher status position in their community tend to be more open to new ideas and have a higher chance to gather information about the innovation (Chan and Misra 1990; Venkatraman 1989). This in turn decreases the uncertainty for the others and they tend to adopt more easily (Herbig and Palumbo 1994). The idea is that high status individuals adopt innovations relatively early, and then based on the interpersonal communications with these high status individuals, others imitate their behavior. Because high status individuals are perceived as having greater product knowledge and familiarity with the product's potential risks, as a result of their constant exposure to media (Moldovan and Goldenberg 2004; Rogers 2003; Venkatraman 1989), potential adopters (e.g., low status individuals) seek to emulate the adoption behavior of higher status individuals (Tarde and Parsons 1903). This implies a high interpersonal communication effect (q). Hence, the following is hypothesized:

H_{3a}: *Social status has a stronger positive effect on aggregate adoption when personal interaction and network externalities are more pronounced than media exposure and social pressure; this will result in an accelerated S-shaped diffusion curve.*

Risky investments frequently prevent individuals from adopting a new innovation. The concept of perceived risk often used by consumer researchers defines risk in terms of the consumer's perceptions of the uncertainty and adverse consequences of buying a product (Dowling and Staelin 1994). In this study, perceived risk is defined as the expectation of losses associated with the purchase of a new product (Peter and Ryan 1976). The role of risk in adoption has been well documented in the literature. Arndt (1967), Popielarz (1967), and West (1990) argued that differing attitudes toward perceived risk is an important feature in distinguishing adopters from non-adopters. Dewar and Dutton (1986) found that the riskiness of the innovation is related to how radical it is. Because individuals are naturally cautious in approaching a novelty, the rate of adoption of an innovation, all other factors being equal, increases as its novelty decreases (Greve 1998). Hence, gathering information in new purchase situations is far more important for first-time individuals. When familiarity of an innovation is increased, for instance by interpersonal communication and the opinion of experts, the perceived risk by an adopter is substantially reduced because of increased accumulated knowledge of the innovation, facilitating adoptive behavior (Meyer and Rowan 1977; Mizruchi 1993; Newell and Jacky 1995). Being familiar with the outcome of an innovation can be acquired by observing the outcomes of other actors, depending on the connectedness of individuals in a network (Bobrowski and Bretschneider 1994; Coleman, Katz, and

Menzel 1966). Learning through such observation lowers the risk of adoption by eliminating novelty or uncertainty of outcomes (Galaskiewicz and Burt 1991; Valente 1995). Therefore, one should expect to have higher q values, which leads to the following hypothesis:

H_{3b}: *Perceived risk has a stronger negative effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externalities; this will result in a decelerated S-shaped diffusion curve.*

4. Innovation and Multi-country Diffusion

As competition increases, more firms are attempting to expand their business overseas. To compete effectively in the global marketplace, managerial interest in understanding adoption processes across countries has grown, especially since several firms that were known for their marketing success struggled when introducing new products into foreign markets (Tellefsen and Takada 1999). An effective international strategy plan is needed to avoid such problems. Therefore, researchers have been studying the underlying factors that are pertinent to the adoption of new products in different countries (e.g., Ganesh, Kumar, and Subramaniam 1997; Gatignon et al. 1989; Heeler and Hustad 1980; Helsen and Schmittlein 1994; Mahajan and Muller 1994; Takada and Jain 1991; Talukdar et al. 2002). These studies have indicated that new products diffuse at significantly different rates in different countries. For example, Heeler and Hustad (1980) noted that the Bass model parameters varied by country and concluded that communication patterns and economic restraints may explain the differences between countries. Similarly, some other researchers have found that new products diffuse more slowly in the United States than in Asia (Takada and Jain 1991) or Europe (Farley and Lehmann 1994). Researchers have also found that new products diffuse at considerably different rates in different European nations (Gatignon et al. 1989; Jain and Maesincee 1995; Mahajan and Muller 1994).

In addition, several factors that may cause these variations have been identified. For example, research suggests that a country's speed of diffusion may be affected by its place in a multi-country roll-out. The first country to receive a new product tends to have a slower diffusion rate than countries that receive the product later (Kalish, Mahajan, and Muller 1995; Mahajan and Muller 1994). Other studies suggest that new product diffusion may be affected by a variety of environmental factors, such as a country's culture (Takada and Jain 1991), cosmopolitanism, mobility (Gatignon et al. 1989), individualism, and uncertainty avoidance (Jain and Maesincee 1995). Though researchers have identified several factors, little is known on how interpersonal communications contribute to adoption of innovations in different countries. This is a gap in the international marketing literature since it has long been accepted that personal interactions play a key role in product adoption and dissemination (Goldenberg et al. 2001b; Moldovan and Goldenberg 2004). The lack of research may be due the fact that gathering data is not easy as information is exchanged in private conversation, making the direct observation difficult. In addition, personal interaction processes are complex in nature. Although the large scale of the system allows the emergence of patterns, which in turn allows one to determine the underlying factors that affect innovation adoption inspired by personal interactions, it is hard to predict empirically (Godes and Mayzlin 2004; Goldenberg et al. 2000; Goldenberg et al. 2001b). Thus, the current study looks at the universal robustness and the applicability of the model developed domestically for international markets.

4.1. Social Interaction and Natural Culture

Although several cultural frameworks have been proposed in the literature (e.g., Clark 1990; Kluckhohn and Strodtbeck 1961; Triandis 1995; Trompennars 1994), the most widely used cultural dimensions are those of Hofstede (2001), whose model is generally accepted as the most comprehensive (Kogut and Singh 1988) and most cited (Chandy and Williams 1994) national culture framework, for which validity, reliability, stability and usefulness have been confirmed over time and in various settings. More importantly, Hofstede's (2001) work is directly applicable to the current work because the norms-and-values approach underlying Hofstede's framework is directly related to the behavioral approach in the current study (see Doney, Cannon, and Mullen 1998).

Hofstede (2001, p. 9) defines national culture as "the collective programming of the mind which distinguishes the members of one category of people from another". Hofstede identified four work-related cultural dimensions along which countries differ. Hofstede's four dimensions are: individualism, power distance, uncertainty avoidance, and masculinity[5]. He argues that a country can be positioned along these four dimensions to provide an overall summary of a country's cultural

[5] The study focuses only on Hofstede's first four dimensions of national culture. The fifth dimension, the long-term orientation, came years after the first four dimensions and has not been extensively used by many of the international innovation adoption researchers. Due to this lack of empirical support (which is critical for initial set up of the model) from past studies, the fifth cultural dimension is excluded from the study.

type. For instance, in general, Australia, Canada, Denmark, Ireland, Great Britain, the Netherlands, Sweden, and the United States are smaller in power distance, more individualistic, more feminine, and weaker in uncertainty avoidance, whereas Argentina, Brazil, Greece, Japan, Mexico, Portugal, Taiwan, Turkey, and Venezuela are larger in power distance, more collectivist, more masculine, and stronger in uncertainty avoidance.

National culture becomes critical here because social interaction referrals that create marketing opportunities in a given country are expected to be different from those of another country because of cultural differences. Again, in this study social processes are composed of four different elements: personal interaction, media exposure, social pressure, and network externality. It is also important to recall from the previous discussion that while media exposure and social pressure are associated with the coefficient of innovation (p), personal interaction and network externality are associated with the coefficient of imitation (q). Building on prior literature, it is hypothesized that each of the social interaction dimensions varies across these four cultural dimensions.

4.1.1. Power Distance

Power distance is defined as the extent to which a society accepts that power in institutions is distributed unequally among individuals (Hofstede 2001). More specifically, power distance measures how subordinates respond to power and authority. In high-power distance countries (e.g., Latin America, France, Spain, most Asian and African countries), subordinates tend to be afraid of their bosses, and bosses tend to be autocratic. In low-power distance countries (e.g., the United States, Great Britain, most of the rest of Europe), subordinates are more likely to challenge bosses and bosses tend to use a consultative management style.

Given that individuals purchase products not only for utility purposes, but also to build a social identity and status (Baudrillard 1981; Douglas and Isherwood 1979), power distance dimension plays a critical role in adoption decisions of individuals. In high-power distance cultures, individuals will follow the adoption behavior of their leader and will adopt new products accepted by their superiors (Tarde and Parsons 1903). In addition, if individuals fear that not adopting a certain innovation may harm their present status in their social group, they are more motivated to adopt the innovation (Burt 1987; Van den Bulte and Stremersch 2004). Taking also into account that individuals from low-powered distance cultures are less open to new ideas and products (i.e., less innovative), individuals from high-power distance cultures will be more associated with the coefficient of imitation (q). Accordingly, Hypothesis 4 is proposed as follows:

H_4: *In high-power distance cultures, personal interaction and network externalities' effects will be more pronounced than those of media exposure and social pressure on adoption decisions when compared to low-power distance cultures.*

4.1.2. Individualism

Individualism is defined as the extent to which people are expected to stand up for themselves as a member of the group (Hofstede 2001). The individualism dimension has drawn quite an interest in cross-cultural consumer behavior research (e.g., Kim et al. 1994; Triandis 1989; Triandis et al. 1988). In individualistic countries (e.g., Canada, France, Germany, and South Africa), independence is highly valued. Individuals are expected to look out for themselves and personal task accomplishment is put before group interest. By contrast individuals in collectivistic cultures (e.g., Greece, Japan, Korea, Mexico, and Turkey) believe they belong to a group, whose overall well being exceeds the needs of the individual. In these cultures, qualities such as loyalty, solidarity, interdependence, conflict avoidance and identification with the group are strongly emphasized (Hofstede 2001).

Individualistic societies tend to form a larger number of looser relationships because a high individualism ranking indicates that individuality and individual rights are paramount within the society. Because of such loose relationships, one would expect that the relative importance of imitative individuals in generating sales for the new product will be less, causing a lower q (Van den Bulte and Stremersch 2004). Using similar logic, individualistic societies, by their emphasis on individual achievement, creativity, novelty and innovation, may tend to use media more extensively than collectivist societies do (de Mooij 1998; Hofstede 2001), which results in higher p values. Previous empirical results also suggest that countries that have higher scores in the individualist dimension will have a higher coefficients of innovation (Van den Bulte and Stremersch 2004; Yaveroglu and Donthu 2002) and a positive influence on the innovativeness of consumers (Steenkamp, Hofstede, and Wedel 1999). This leads to the following hypothesis:

H_5: *In individualistic cultures, media exposure and social pressure' effects will be more pronounced than those of personal interaction and network externalities on adoption decisions when compared to collectivistic cultures.*

4.1.3. Masculinity

Masculinity is defined as the importance placed on traditionally male values (Hofstede 2001). More specifically, masculinity and femininity refer to the sex role pattern in society at large, to the extent that it is characterized by male or female personality (Tellis, Stremersch, and Yin 2003). Masculine cultural values tend towards aggressiveness, assertiveness and self-achievement. On the other hand, feminine values foster care, sympathy and intuition (Hofstede 2001; Tellis et al. 2003).

A high masculinity ranking indicates that the country experiences a high degree of gender differentiation. In these cultures, males dominate a significant portion of the society and power structure, with females being controlled by male domination. Because masculine cultures put more emphasis on wealth, material success, and self-achievement (de Mooij 1998; Steenkamp et al. 1999), display of status and material possessions are more common in masculine cultures than in feminine cultures (Van den Bulte and Stremersch 2004). One symbolic means of demonstrating achievement is by having the latest and most novel product, hoping that new products bring success and ultimately higher status in the society. To ensure a higher status in their society, individuals in masculine cultures therefore are more motivated to find innovations that create clear dissimilarity between them and others (Stremersch and Tellis 2004). Hence, these individuals tend to gather information about innovations in every way, which requires interacting with other members of the society. This implies a positive relationship between masculinity and q. Therefore:

H_6: *In masculine cultures, personal interaction and network externalities' effects will be more pronounced than those of media exposure and social pressure on adoption decisions when compared to feminine cultures.*

4.1.4. Uncertainty Avoidance

Uncertainty avoidance is defined as the extent to which a society feels threatened by ambiguous situations and tries to avoid them by providing particular rules, regulations and religions (Hofstede 2001). High uncertainty avoidance cultures have a low tolerance for uncertainty and ambiguity and exhibit lesser willingness to take risks (Tellis et al. 2003; Yeniyurt and Townsend 2003). Societies that are high in uncertainty avoidance continuously feel the inherent ambiguity in life while societies low in uncertainty avoidance more easily accept ambiguity (Stremersch and Tellis 2004; Van den Bulte and Stremersch 2004; Yaveroglu and Donthu 2002). This means societies that are low in uncertainty avoidance are more willing to take risks. Therefore, one would expect high coefficient of imitation (i.e., q) values in high uncertainty avoidance cultures since potential adopters can learn of a new product's features and possible risks associated with uncertainty by interacting with the people who have already adopted the product. Such a behavior reduces potential adopters' uncertainty and motivates their adoption of the new product (Stremersch and Tellis 2004; Van den Bulte and Stremersch 2004). Because reduction in uncertainty is more essential for high-uncertainty avoidant cultures than low-uncertainty avoidant cultures, members of the high uncertainty cultures are more influenced by prior adopters than members of low uncertainty avoidance cultures, which lead to higher q values. Therefore, the following is hypothesized:

H_7: *In high-uncertainty avoidance cultures, personal interaction and network externalities' effects will be more pronounced than those of media exposure and social pressure on adoption decisions when compared to low-uncertainty cultures.*

CHAPTER 4

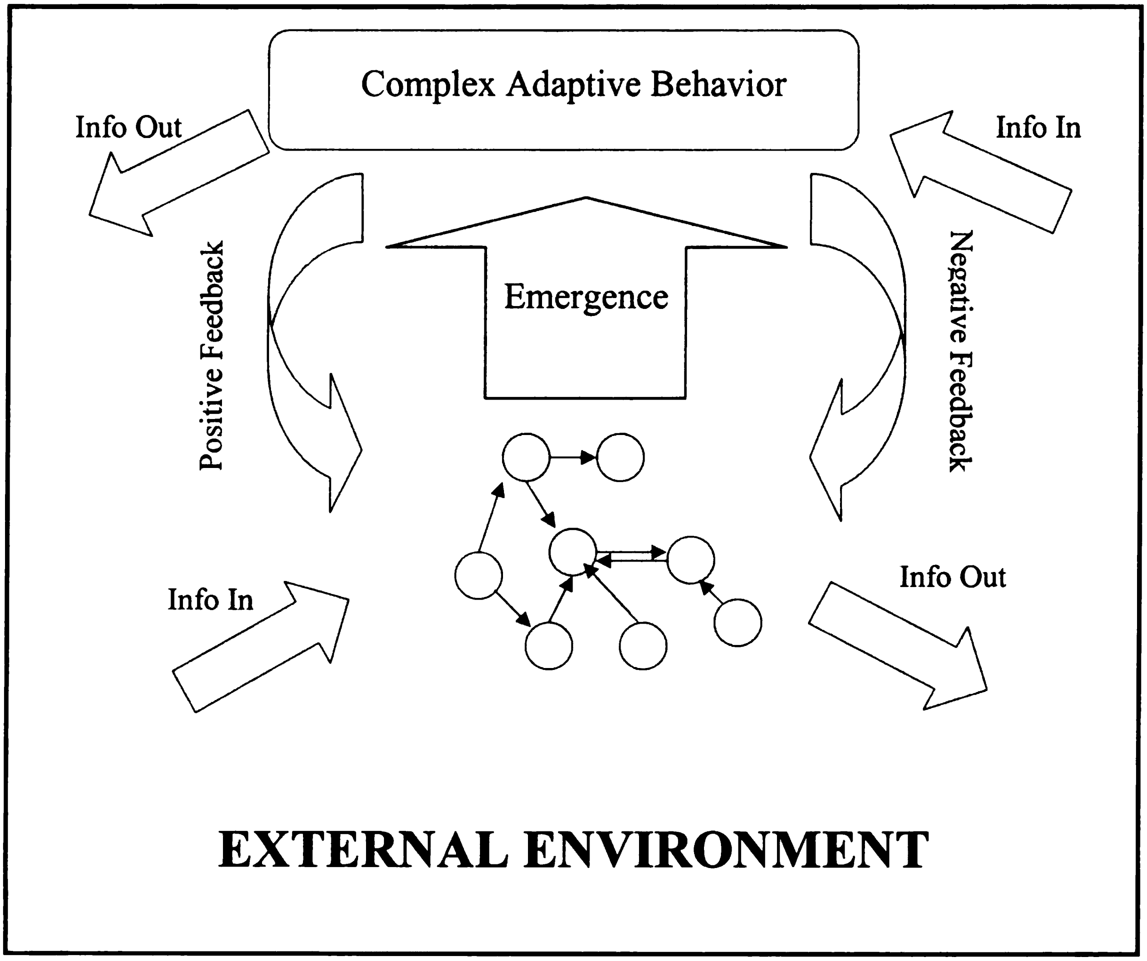
METHODOLOGY

1. Complex Adaptive Systems: Agent-Based Modeling Approach

Complex adaptive systems (CAS) are commonly defined as systems that consist of a large number of interacting individuals, ultimately generating collective behavior at the aggregate level (Moldovan and Goldenberg 2004; Waldrop 1992). These systems are *complex* in that they are diverse and made up of multiple interconnected elements and *adaptive* in that they have the capacity to change and learn from experience. The strength of complex adaptive systems derives from its ability to bring micro and macro social phenomena together and capture the underlying details of unexplained behavior (Garcia 2005; Morel and Ramanujam 1999). An illustration of complex adaptive behavior is shown in Figure 3[6].

[6] Figure 3 is adopted from wikipedia.org

Figure 3: Illustration of Complex Adaptive Behavior



Although CAS has been used extensively in modeling physical, chemical, and biological systems, they have only recently been accepted within the marketing sciences. Despite the fact there is a long tradition of using simulations in the innovation diffusion research (e.g., Frenzen and Nakamoto 1993; Garcia, Calantone, and Levine 2003; Levinthal and March 1981), the role of complex adaptive systems has largely been neglected in the diffusion of innovations literature (with the exception of some recent studies, e.g., Garcia 2005; Goldenberg, Libai, and Muller 2002; Goldenberg et al. 2001b; Moldovan and Goldenberg 2004). Frenzen and

Nakamoto (1993) provide a good example of how individual level simulation modeling can lead to a better understanding of aggregate level trends. However, their model does not take into account social interactions among individuals.

One methodology for studying complex adaptive systems is *agent-based modeling*. Characteristics of agent-based modeling (ABM), along with differences between agent-based modeling and other simulation techniques, are discussed in the following sections.

1.1. Properties of Agent-Based Modeling

An agent-based model consists of a system of agents (decision-making entities) and the relationships between them. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. The behavior of the system is the outcome of the repetitive interactions among the agents. Agent-based modeling has proved especially useful in understanding complex social dynamics, notably those involving interactions between micro- and macro-level processes and the development of emergent behaviors, such as the diffusion of innovations, emergence of norms, participation in collective actions and knowledge/information flows (Bonabeau 2002; Tesfatsion 2002). The central issue being explored in these kinds of applications is the way in which agents respond to their social context, specifically to how others around them are acting (Bonabeau 2002). Even a simple agent-based model can exhibit complex behavior patterns and provide valuable information about the dynamics of the real-world system that it emulates.

Agent-based modeling provides a number of advantages over other simulation methods. The most noticeable advantage of ABM is its ability to incorporate dynamic internal and external elemental environment influences in the adoption process. In ABM, the unit of study is the agent (individuals, in this study). The agents interact with each other along with their environment and represent heterogeneous entities (Bonabeau 2002; Epstein 2002). This heterogeneity aspect of agents allows a more realistic demonstration of real-world phenomena than models that assume homogeneity since each agent (i.e., an individual) has a unique way of assessing and reacting to internal and external influences on adoption decisions.

Complex systems may be seen as exhibiting any of a set of basic properties. However, the two most commonly observed properties of complex systems are the large number of interacting elements and emergent behaviors. Complex systems generally consist of a large number of elements that interact with one another to form nonlinear macro-behavior. Such interactions are typically coupled with the presence of feedback mechanisms in the system. These interactions in turn introduce nonlinearities into the dynamics of the system (Casti 1997). The main idea is to understand how relationships between parts give rise to the collective behaviors of a system and how the system interacts and forms relationships with its environment.

In addition to the presence of a large number of interacting components, complex systems exhibit emergent behaviors (i.e., the appearance of patterns which are due to the collective behavior of the components of the system). It is generally accepted that the whole is more than the sum of its parts in emergent systems (Holland 1998; Tesfatsion 2002). That is, unsystematic macro-level events can take place based on changes at the micro-level. The ABM approach is particularly suitable to modeling innovation diffusion processes, in which aggregated adoption behaviors "emerge" from heterogeneous and complex interactions among "agents" (individuals in the potential population). Here, the current study offers a technique for bridging micro level innovation adoption and macro level innovation diffusion, employing stochastic cellular automata, a modeling approach consists of cells on a grid of specified shape that evolves through a number of discrete time steps according to a set of rules based on the states of neighboring cells.

1.2. A Cellular Automata Model

In order to study the dynamics of complex systems, social science researchers rely heavily on the use of mathematical modeling and computer simulations. Cellular automata (CA) are particularly useful analytical tools used within complex systems (Casti 1997; Wolfram 1984). Cellular automata is a technique for complex systems modeling that simulates aggregate consequences based on local interactions among members of a population. The elements of a typical simulation are a certain number (ranges from 5 to 5000) of interactive agents and a set of rules based on interactions among agents. The model usually starts with some initial condition set by a researcher; the simulation consists in applying the rules through several iterations. The models track members' changing states and parameters over time. Thus, cellular automata is different from other alternative modeling techniques that use individual characteristics to compute average population attributes and then simulate changes in the population (for detailed description of this technique, see Adami 1998; Goldenberg et al. 2001a; Von-Neumann 1966).

A cellular automata model describes the social system as a matrix of cells, each of which represents an individual who is able to receive information and make decisions based on the information. Here, the CA model is composed of an array of cells, each having discrete values of 0 and 1 representing the state of each individual: state 0, representing the *potential adopters* who have not adopted the innovation and state 1, the *adopters* who have adopted the innovation. Figure 4 depicts an example of such an environment.

Figure 4: Illustration of Cellular Automata Process

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Before Launch

0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0
0	1	0	0	0	0	0	0
0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1

At Introduction

1	1	1	1	0	1	1	1
1	0	1	1	1	1	1	1
1	1	1	1	1	0	1	1
0	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1
1	1	0	1	1	1	0	1
1	1	1	1	1	1	1	1
1	1	1	1	1	0	1	1

At Maturity

Notes: A vale of 0 represents a potential consumer who has not adopted the innovation while a value of 1 represents a consumer who has adopted the innovation

Following, a general overview of the model is proposed. Then, more details about the parameters and step-by-step outline of the cellular automata algorithm are given.

1.2.1. The principles of the model are the following:

1) The model consists of *n* number of virtual individuals in a given simulated social system, each of whom is able to receive information during consecutive, discrete periods. A social system is characterized as an array of cells (each cell represents an individual) within a grid. Each individual situated within a grid has eight neighbors; four immediate neighbors (north, south, east, and west) and four distant neighbors (northeast, northwest, southeast, and southwest). Unlike Axelrod (1997)'s dissemination of culture model, the current model is designed as a grid without edges. In this case, all individuals have the same number of neighbors.
2) Individuals are related to each other through social interactions, which can be more or less dense. Individuals were distributed geographically in fixed locations. The innovation diffusion literature suggests a clear correlation between geographic proximity and the strength of word-of-mouth influences (Granovetter 1978; Rogers 2003). Because individuals are more closely tied to their immediate neighbors than their distant neighbors, they learn more about the innovation's attributes from their immediate neighbors (Brown and Reingen 1987; Goldenberg et al. 2001b). In this study, a precise influence of the network structure is not examined; rather results related to the density of social interactions are investigated. An underlying assumption is that all potential adopters are capable of interaction with each other.

3) At each period, an individual falls into one of the five adopter categories with a given probability. The likelihood of an individual to belong to *Innovators, Early Adopters, Early Majority, Late Majority*, and *Laggards* categories is 2.5, 13.5, 34, 34, and 16 percent respectively. These are acceptable percentages taken from innovation diffusion theory (Rogers 2003)[7], and all probabilities are equivalent to these percentages.
4) The heterogeneity of individuals is established by randomly setting individual characteristics (i.e., social status and risk tolerance of individuals). In addition, mean and standard deviation are employed to achieve even further heterogeneity among individuals.
5) In the initial stage of the model, all individuals are in the "potential adopters" state (i.e., state 0).
6) Irreversibility of transition is assumed, so that individuals who adopt the innovation cannot change their mind and become *potential adopters* again.
7) It is assumed that the mass media regularly communicates messages about the innovation, reaching individuals at random, with a given frequency. Individuals who receive the messages tend to communicate messages to each other containing their opinion about the innovation, and a propagation of the interactions in the social network is modeled. It is assumed that the information enables individuals to evaluate the individual benefits of adopting an innovation.
8) Consistent with prior literature (e.g., Buttle 1998; Goldenberg et al. 2001b), the probability of being affected by media exposure (i.e., advertising,

[7] For detailed characteristics of each adopter categories, please see Appendix B.

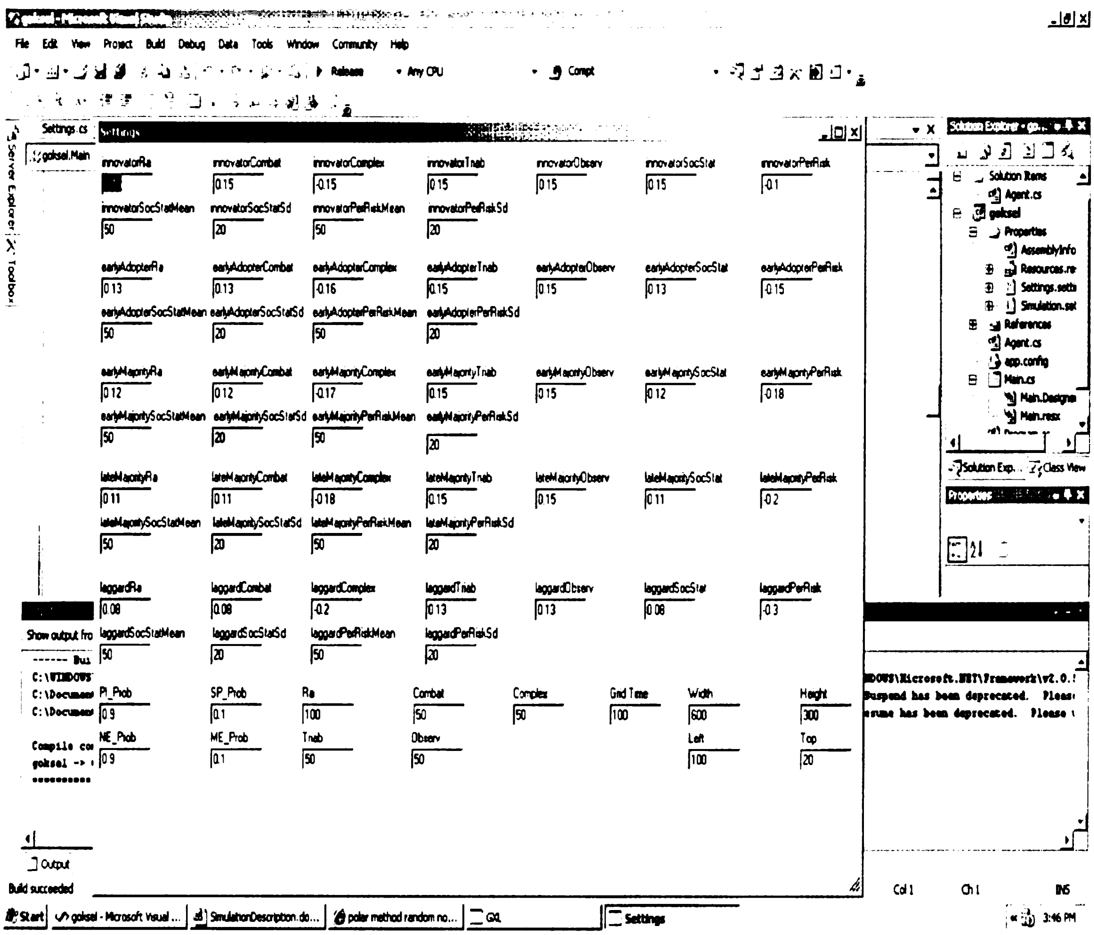
promotion, and other marketing efforts)[8] is assumed to be smaller than the effect of interpersonal interactions (i.e., word-of-mouth).

9) It is postulated that individuals may influence each other's adoption decisions only if they have interactions.
10) Following innovation diffusion theory and previous research (e.g., Rogers 2003; Valente 1995), individuals who have higher status interact with more individuals and their interactions have more influence.
11) When individuals gain information about the innovation through both media and local interactions with their colleagues, they evaluate the potential benefits of adoption.
12) The transition from a potential adopter to adopter depends on the intrinsic attributes of the innovation (i.e., relative advantage, compatibility, complexity, trialability, and observability), distinct characteristics of individuals, as well as number and behavior of neighbors.
13) It is also assumed that the individual level parameters are related to the aggregate-level ones (Goldenberg et al. 2002; Goldenberg et al. 2001a).
14) The model is solved computationally by running a stochastic process, in which each individual's probability of adoption (i.e., the transition from state 0 to state 1) is determined at each period.

A snapshot from simulation is provided below.

[8] Although it is generally believed that external factors represent marketing variables in the diffusion literature, in reality they can represent any influence other than social interactions.

Figure 5: A Snapshot from Simulation Settings



It is important to point out that the perceived risk and social statuses are calculated using the Polar Method. The Polar Method use provided mean and standard deviation to generate a number that would be somewhere on the distribution curve. The distribution of the random numbers generated by the Polar Method creates a bell curve around the provided mean, with the width heavily influenced by the standard deviation.

Figure 6: Bell Curve Generated Using Polar Random Normal Method

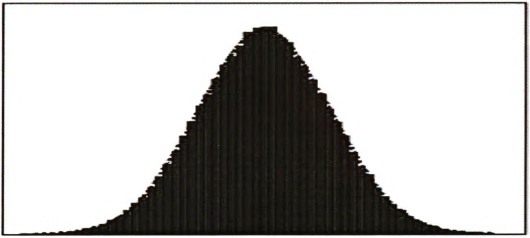
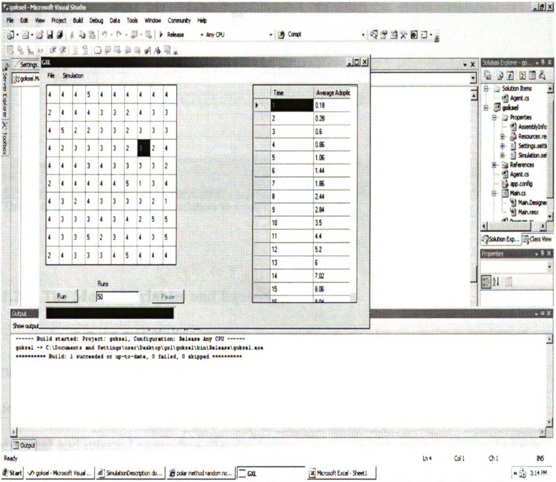
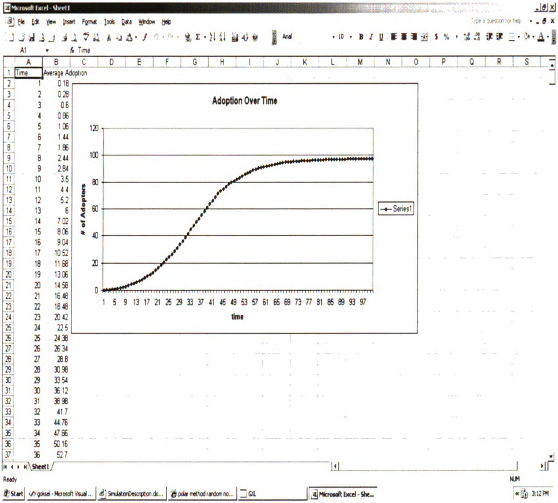


Figure 7: A Snapshot from Simulation Settings



The grid on the right represents the agents for the current run and their corresponding Rogers's category. The table on the left represents the average number of adopters at time T.

Figure 8: A Snapshot from Simulation Results



This is the final output of the simulation to excel.

1.2.3. The Model Variables and Equations

Within the marketing literature, the modeling of the aggregate diffusion of new products typically follows the Bass (1969) model. The Bass model in turn follows Rogers's innovation diffusion theory, which highlights the importance of external and internal communication influences as well as the unique characteristics of an innovation as driving forces of new product adoption. External influences, represented by probability *p*, assert that an individual will adopt the innovation as a result of marketing efforts such as advertising, promotions, and mass media. Internal influences, represented by probability *q*, stress that an individual will adopt the innovation because of a social interaction with other individuals.

Then, the probability of an individual to adopt a new product at time *t*, $\text{AdoptionProb}_{(t)}$, is based on the following formula:

$$\text{AdoptionProb}_{(t)} = [1 - (1\text{-p})\,(1\text{-q})^{k(t)}] \qquad (1)$$

where *k(t)* is the number of previous adopters at time *t*.

Consistent with prior discussion, for individuals to move from potential adopter state to adopter state depends on three main factors: a) the characteristics of the innovation such as relative advantage, compatibility, complexity, trialability, and observability; b) the idiosyncratic characteristics of individuals (e.g., risk tolerance and social status); and c) the intensity of internal and external forces within the market (e.g., personal interaction, media exposure, social pressure, and network externalities). Following the theory and previous arguments (see Hypotheses Development section), one can argue that while compatibility, complexity, trialability, media exposure, and social pressure are associated more with *p* (i.e., coefficient of innovation), relative advantage, observability, social status, perceived risk, personal interaction, and network externalities are associated more with *q* (i.e., coefficient of imitation). As such, p is set as a multiplicative function[9] of each of the associated attributes:

$$p = e^{\beta_0} \cdot COM^{\beta_{COM}} \cdot COMX^{\beta_{COMX}} \cdot TRA^{\beta_{TRA}} \cdot e^{\beta_{ME}} \cdot e^{\beta_{SP}} \qquad (2)$$

where

β_{COM} = the adoption probability that an individual will be affected by compatibility attributes of an innovation,

β_{COMX} = the adoption probability that an individual will be affected by complexity attributes of an innovation,

β_{TRA} = the adoption probability that an individual will be affected by trialability attributes of an innovation,

β_{ME} = the adoption probability that an individual will be affected by media exposure, and

β_{SP} = the adoption probability that an individual will be affected by social pressure.

Similarly, q is set as a multiplicative function of each of the associated attributes:

$$q = e^{\beta_0} \cdot RA^{\beta_{RA}} \cdot OBS^{\beta_{OBS}} \cdot SS^{\beta_{SS}} \cdot PR^{\beta_{PR}} \cdot e^{\beta_{PI}} \cdot e^{\beta_{NE}} \qquad (3)$$

where

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[9] To learn more about the use of multiplicative functions, see Elberse and Eliashberg's (2003) study on motion pictures. In this study, the weekly revenues of a movie are modeled as a multiplicative function of word-of-mouth influence, competition for the attention of audiences, and season.

β_{RA} = the adoption probability that an individual will be affected by relative advantage attributes of an innovation,

β_{OBS} = the adoption probability that an individual will be affected by observability attributes of an innovation,

β_{SS} = the adoption probability that an individual will be affected by her/his social status within his/her environment,

β_{PR} = the adoption probability that an individual will be affected by her/his risk tolerance level,

β_{PI} = the adoption probability that an individual will be affected by personal interaction, and

β_{NE} = the adoption probability that an individual will be affected by network externality.

Once the simulation starts, the following steps are executed repeatedly until the model converges to equilibrium:

Step 1: This is the initial condition, in which none of the individuals has yet adopted the product (receiving the value of 0).

Step 2: The probabilities for each individual $AdoptionProb_{ti}$ are realized. Only media influence (e.g., advertising) is at work during this period, because personal interaction requires individuals who have already adopted the product to start the process. A random number of *Randomization* is drawn from a uniform distribution in the range [0, 1]. If *Randomization* <= $AdoptionProb_{ti}$, then the individual moves from potential adopter to adopter (receiving the value of 1). Otherwise, the individual remains a potential adopter.

Step 3: The individuals who have adopted the product begin the word-of-mouth process by deploying communications within their social networks. Probabilities are realized as in Period 1, and the random number is drawn so that when *Randomization* <= $AdoptionProb_{ti}$, the individuals move from potential adopter to adopter state.

Step n: This process is repeated until a cumulative number of adopters do not change after five runs.

In the next section, we conduct two studies to test the hypotheses presented in the previous sections. The first study investigates the combined effect of unique product and individualistic characteristics on adoption decisions under the changing external environment. Specifically, the study explores how individual level differences contribute to aggregate level parameters. The second study investigates the linkage between macro-level adoption and macro-level diffusion in international settings.

2. The First Study – Domestic Adoption Behavior

The first study explores the joint effects of innovation and individual characteristics on adoption decisions under different levels of social process dimensions. By examining the joint effects, this study provides a baseline model and a more comprehensive understanding of dynamics that are pertinent to the adoption of innovations. Emphasis is given to these factors because the main contention of this study is that aggregate level diffusion patterns can be explained if one can understand the variations at the individual level. As such, the study links the two divergent research streams, namely macro-level diffusion studies and micro-level adoption studies.

2.1. Method

It should be noted that it is essential to define a proper range of parameters when working with simulations such as the cellular automata modeling used in this study. In the area of new products adoption at the individual level and diffusion at the aggregate level, the Rogers and the Bass models respectively are the ones that provide a large body of empirical data. Therefore, it is reasonable to use the parameter ranges derived from this body of knowledge to calibrate the model's parameter range. To maintain validity, the current study uses previous research on the values of the Rogers's product innovation characteristics parameters (Moore and Benbasat 1991; Tornatzky and Klein 1982). Tornatzky and Klein (1982) found that relative advantage, compatibility, and complexity had the most consistent significant relationships to innovation adoption and this finding is reflected in the model. Parameter ranges for product innovation characteristics are set as follows:

Effect of relative advantage (β_{RA})	0.04 ; 0.38
Effect of compatibility (β_{COM})	0.08 ; 0.46
Effect of complexity (β_{COMX})	-0.02 ; -0.34
Effect of trialability (β_{TRA})	0.01 ; 0.17
Effect of observability (β_{OBS})	0.005 ; 0.11

Similarly, the range of the other parameters is chosen based on the diffusion literature. Parameters p and q are determined according to prior studies. The average value of p has been found to be 0.03, and is often less than 0.01 while the average value of q has been found to be 0.38 with a typical range between 0.3 and 0.5 (Goldenberg et al. 2002; Mahajan, Muller, and Bass 1995; Sultan et al. 1990). The assumption is that the individual level parameters relate to the aggregate level ones. As it is explained in previous studies (Goldenberg et al. 2002; Goldenberg et al. 2001a), the values of p between the individual level probabilities and the aggregate level parameters are fairly close to each other because they both represent probabilities of adoption as influenced by external factors such as media. Thus, the boundaries are set for p ranging from 0.005 to 0.05. The case of q is more complicated as q at the individual level provides a slightly different meaning than q at the aggregate level. At the individual level, q is the probability that a certain potential adopter will be affected by *one* previous adopter. Given that many potential adopters exist, q at the individual level is expected to be much lower than q at the aggregate level in order to achieve a similar effect. Hence, the boundaries of q are set in between 0.00005 and 0.005. In addition, consistent with the assumption that an individual holding a higher status in a community will take much more risk associated with an innovation, social status and risk tolerance of an individual toward the innovation are set as negatively correlated.

A computer model for this study is programmed in the C# (i.e., C Sharpe) language.[10] The purpose of this model is to explore the effects of all available parameters on the innovation diffusion and its slope. In each run, the population consists of 100 potential adopters, and the population is divided into five adopter categories with respected percentages (see Appendix B). All members of the population are in a "*potential adopter*" state initially. For each period, the status change of each consumer is assessed on the basis of the probability described above (Equations (1) – (3)). The values are substituted for each parameter based upon ranges consistent with prior studies as explained in the previous section. All of the results presented in this section are averages based upon 100 runs.

2.2. Simulation Results

The cellular automata model indicated several important properties that would be expected to illustrate innovation diffusion processes within markets. First, although each of the innovation characteristics has an influence on adoption decisions, these influences are "sub-optimal" in a sense that after a certain point, contribution of innovation characteristics is negligible. This finding is also true for the dimensions of social processes (i.e., personal interaction, media exposure, social pressure, network externality). After a certain point, a dominant influence of each of the dimensions' effects on adoption indicates diminishing returns.

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[10] Program details are available from the author.

Second, beyond the relatively early stages of the adoption process, the effect of marketing efforts (e.g., advertising, promotion) quickly diminishes and personal interactions (e.g., word-of-mouth) become the main forces driving the adoption process. This result is very much inline with previous findings, which argued that personal interactions are the main forces driving the speed of innovation diffusion (Goldenberg et al. 2001b; Rogers 1995). Third, the proportion of adopters to the population increased with the size of the population (*n*) as different opinions create greater opportunities for individuals to be familiar with an innovation in larger populations. Different view points of innovation in a population generates a high level of collective knowledge as individuals tend to place more weight on opinions that improve upon prior information (Miller, Zhao, and Calantone 2006). These variations suggest that an individual who is connected to a group of innovators has a higher chance of gathering product related information.

2.2.1. Effects of Innovation Characteristics on Adoption

To show the implications of altering the product innovation and individualistic characteristics, the cellular automata model is set with low and high levels of social process dimensions on adoption decisions. H_{1a} predicts that relative advantage has a stronger positive effect on aggregate adoption when personal interaction and network externatilities are more pronounced than media exposure and social pressure. Figure 9a shows the effect of relative advantage attribute of product innovation on adoption decisions under varying degrees of social process dimensions. At low levels of relative advantage when personal interactions and network externalities are high and social pressure and media exposure are low, adoption progresses very slowly. In fact, the diffusion curve does not even provide a clear S-shaped diffusion. A high value of relative advantage under the same conditions provides a much more traditional S-shaped diffusion curve with take-off after period 15. The diffusion of an innovation occurs rapidly, and the slope of the S-shaped diffusion curve is steep. Figure 9b (personal interaction and network externality are low while social pressure and media exposure are high) indicates that the diffusion of the innovation happens even sooner and the slope of the S-shaped diffusion curve is steeper under the high value of relative advantage. One possible explanation for this rapid diffusion would be the importance of intense marketing efforts (i.e., media exposure) for adoption at early stages of product life cycle.

Figure 9a: Effect of Relative Advantage on Adoption Decisions When Personal Interaction and Network Externality Are High While Social Pressure and Media Exposure Are Low

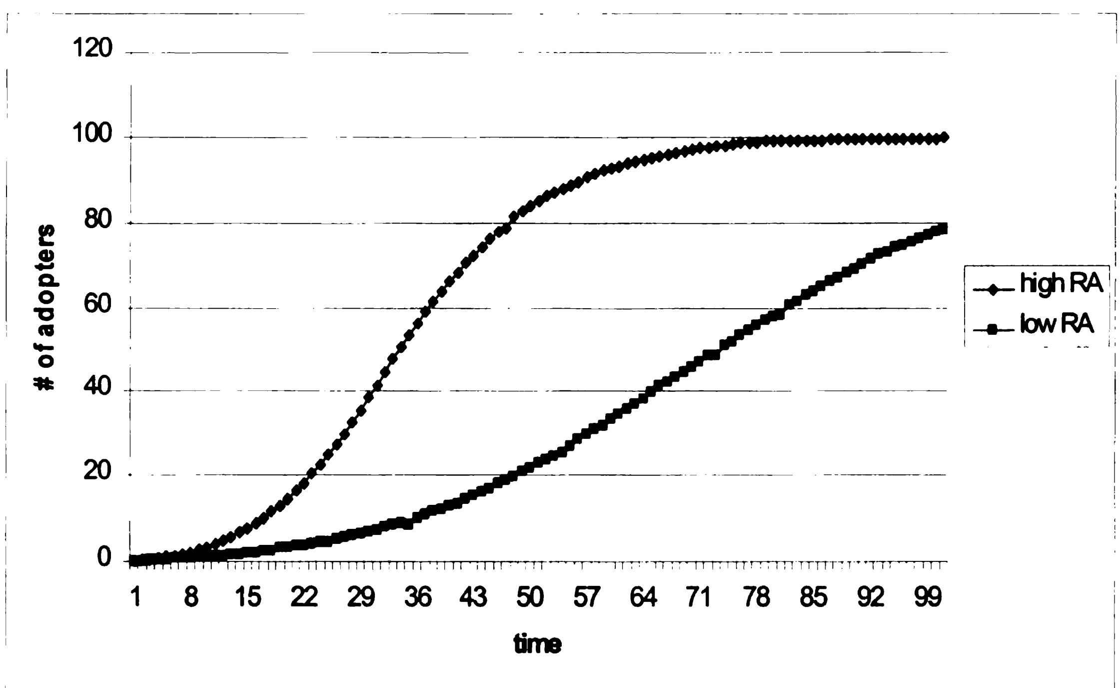
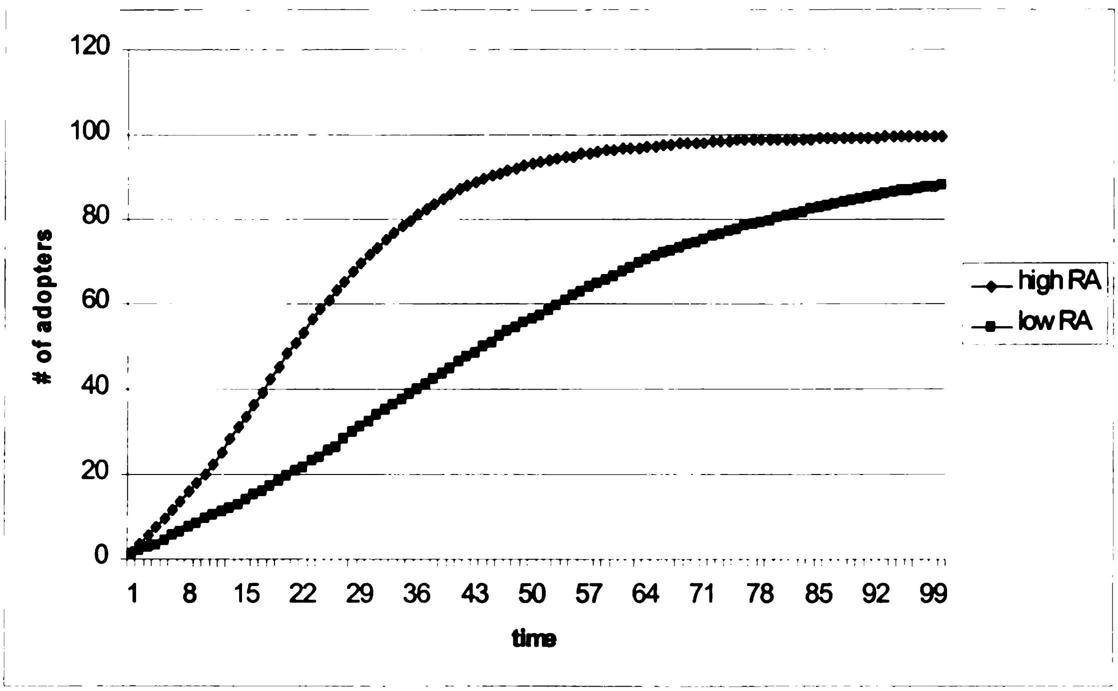


Figure 9b: Effect of Relative Advantage on Adoption Decisions When Personal Interaction and Network Externality Are Low While Social Pressure and Media Exposure Are High



Although this result shows the importance of relative advantage on adoption decisions, more interesting results emerge with the varying values of social process dimensions. Figure 9a and 9b show the contrasting results for high and low levels of relative advantage under the different levels of social process dimensions ($\beta_{PI} = 0.7$, $\beta_{NE} = 0.7$, $\beta_{SP} = 0.3$, and $\beta_{ME} = 0.3$ for Figure 9a, and $\beta_{PI} = 0.3$, $\beta_{NE} = 0.3$, $\beta_{SP} = 0.7$, and $\beta_{ME} = 0.7$ for Figure 9b). The distance between the diffusion curves obtained when a relative advantage is high versus low is greater in Figure 9a than that of Figure 9b, indicating that personal interactions and network externalities are more important social process dimensions than social pressure and media exposure for recognizing the value of relative advantage attributes of product innovation on adoption decisions. An Analysis of Variance (ANOVA) was also conducted in SPSS 14.0 for Windows to check for differences mentioned above. The Levene statistic (45.928, $p < 0.001$) indicates that the two groups cannot be assumed to have homogenous variance. Because the assumption of equal variances is violated, a t-test for independent samples where equal variances are not assumed was also conducted. Results of the t-test for independent samples and ANOVA are consistent with each other (Appendix D). The results of the t-test indicate that the means of the two groups are different ($M_{group1} = 35.54$, $M_{group2} = 24.97$; $t\ (154.503) = 4.460$, $p < 0.001$)[11]. Similarly, the results of the ANOVA indicate that the means of the two groups are different ($M_{group1} = 35.54$, $M_{group2} = 24.97$; $F\ (1,198) = 19.888$, $p < 0.001$). The result supports the first hypothesis, (i.e., H_{1a}).

H_{1b} states that observability has a stronger positive effect on aggregate adoption when personal interaction and network externatilities are more pronounced than media exposure and social pressure. Figure 10a and 10b illustrate the effects of the observability attributes on diffusion under different levels of social process dimensions. As shown in Figure 10a and 10b, a lower level of observability produces the diffusion curve that is more horizontal than the one that was produced with a higher level of observability, indicating that an innovation diffuses faster with a high level of observability. In early periods, adoption is very limited with a few individuals. After period 25, the diffusion increases, although the slope of the curve is not all that sudden. This finding corresponds with Tornatzky and Klein's (1982)

[11] Group 1 is the distance between the diffusion curves attained when a relative advantage is high versus low under the influence of high personal interaction and network externality, and low social pressure and media exposure. Group 2 is the distance between the diffusion curves attained when a relative advantage is high versus low under the influence of low personal interaction and network externality, and high social pressure and media exposure.

finding that observability's role on adoption decisions is not as strong as that of relative advantage. In addition, as Figures 11a and 11b illustrate the gaps in between the S-shaped curves generated by high and low levels of observability seem negligible. This observation is statistically confirmed with the results of the t-test and ANOVA (Appendix E). T-test results indicate that the means of the two groups are not significantly different ($M_{group1} = 7.98$, $M_{group2} = 6.44$; $t(189.821) = 1.333$, $p > 0.001$). Likewise, the results of the ANOVA show that the means of the two groups are not different ($M_{group1} = 7.98$, $M_{group2} = 6.44$; $F(1,198) = 1.776$, $p > 0.001$). This finding reveals that no meaningful differences are found among the relative importance of the different dimensions of social processes for their role in adoption decisions. Therefore, H_{1b} is not supported.

Figure 10a: Effect of Observability on Adoption Decisions When Personal Interaction and Network Externality Are High While Social Pressure and Media Exposure Are Low

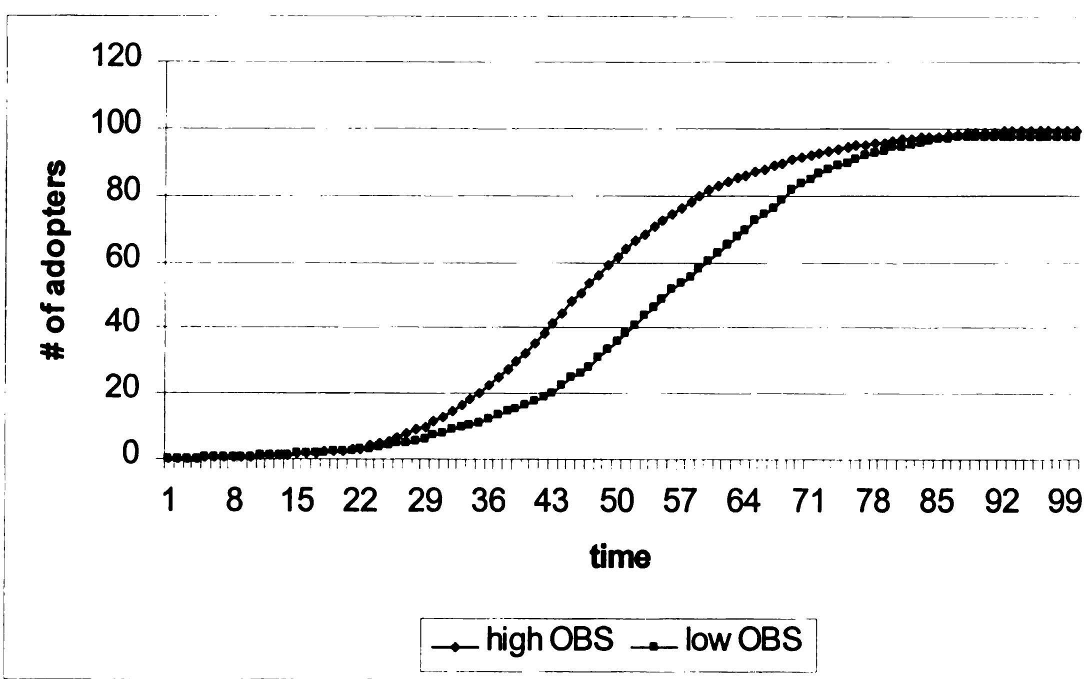
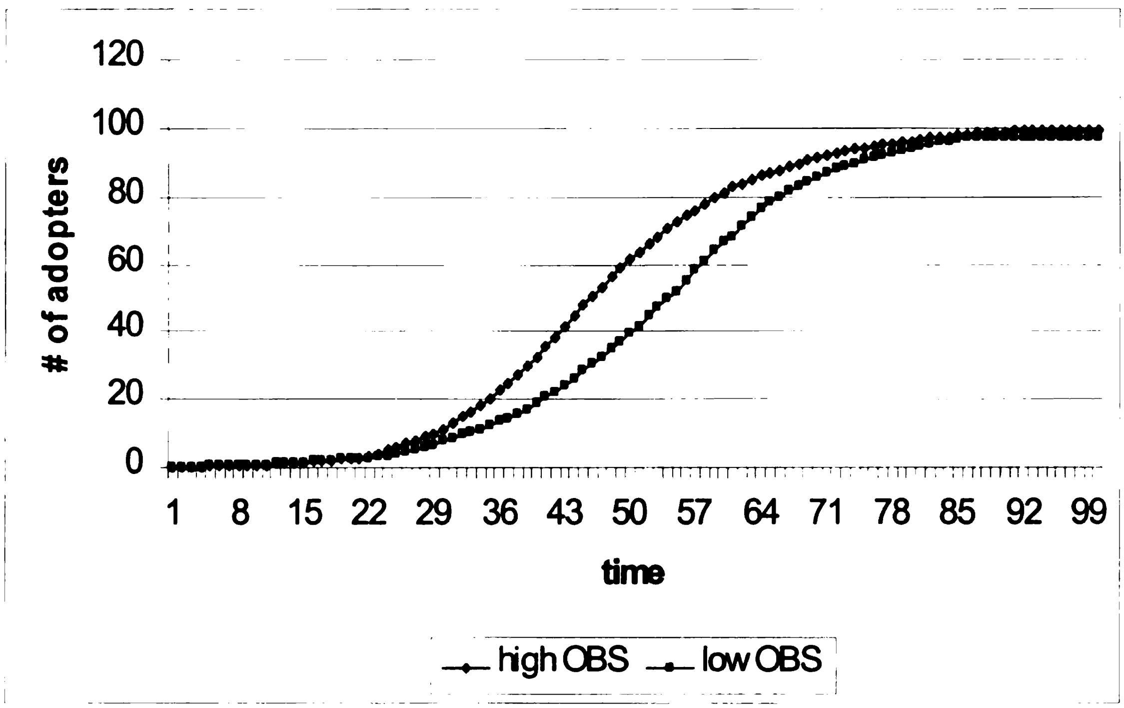


Figure 10b: Effect of Observability on Adoption Decisions When Personal Interaction and Network Externality Are Low While Social Pressure and Media Exposure Are High



Figures 11a and 11b confirm that compatibility is a critical innovation characteristic for adoption of new products. High levels of compatibility with existing knowledge, life styles, experiences, etc. create a far quicker innovation adoption and a diffusion pattern as opposed to low levels of compatibility. As seen from the figures, the adoption and diffusion under high levels of compatibility occur at fairly early stages of the diffusion process (product take off point is after Period 15). In this case, the diffusion curves are near vertical, and the slope of the S-shaped curve is steep. However, under low levels of compatibility, the graphs present two relatively different diffusion curves. In the case where personal interaction and network externality are low while social pressure and media exposure are high (Figure 11a), almost all individuals adopt the innovation after period 80 as was the case under high levels of compatibility. Although the curve suggests that more time is needed for potential adopters to adopt the innovation (take off point is around period 30), the diffusion curve is still S-shaped with a less steep slope. For the other case where personal interaction and network externality are high while social pressure and media exposure are low (Figure 11b), not all potential adopters adopt the innovation after 100 periods. The diffusion curve does not provide any clear take off point and moves along the horizontal lines.

Figure 11a: Effect of Compatibility on Adoption Decisions When Personal Interaction and Network Externality Are Low While Social Pressure and Media Exposure Are High

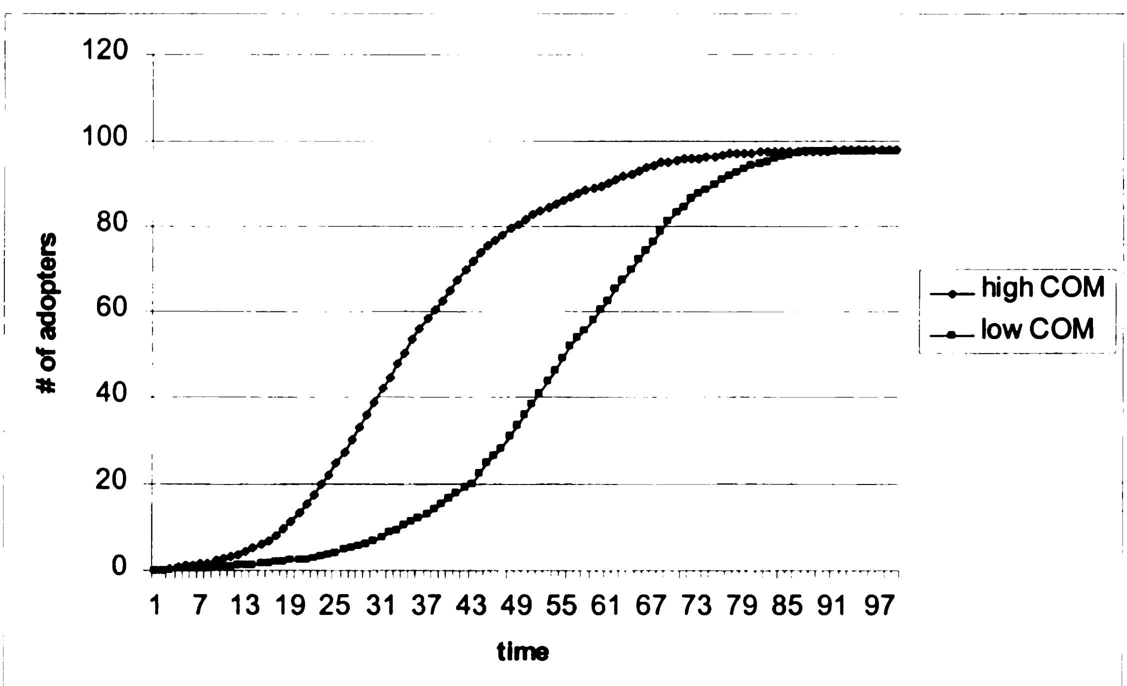
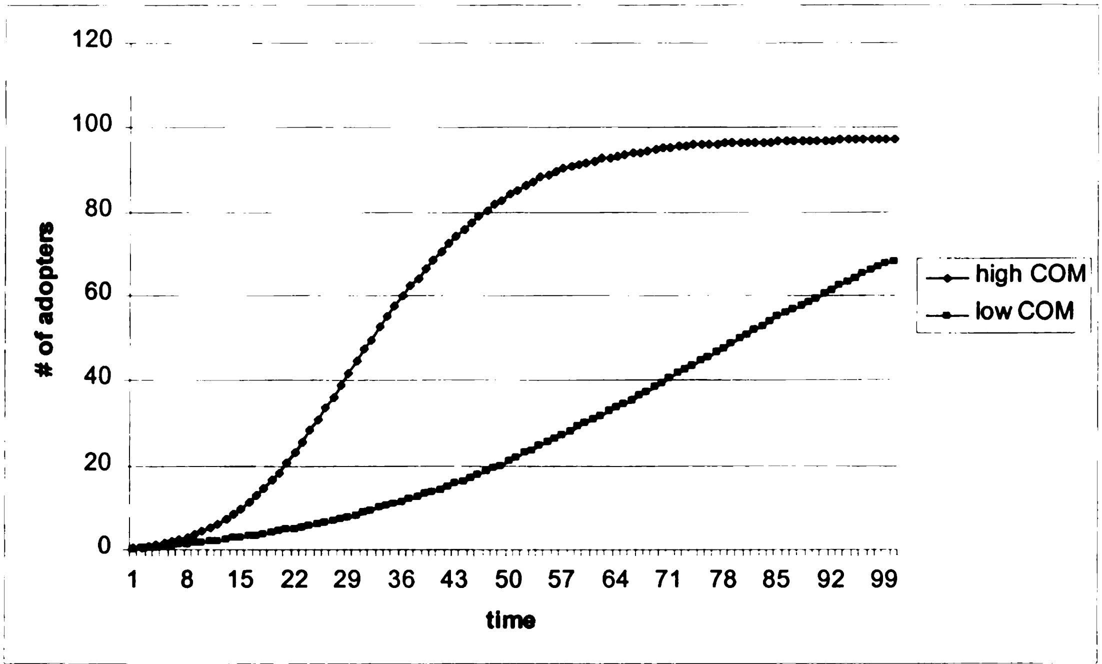


Figure 11b: Effect of Compatibility on Adoption Decisions When Personal Interaction and Network Externality Are High While Social Pressure and Media Exposure Are Low



To show the importance of social pressure and media exposure for recognizing the significance of compatibility on adoption, the model also compares the changing values of four social process dimensions. The space between high and low compatibility curves along the horizontal line under high levels of social pressure and media exposure is far greater than the space between high and low compatibility curves under high levels of personal interaction and network externality, which implies that social pressure and media exposure play an especially important role for recognizing the compatibility of the innovation. The results of the t-test and ANOVA support this finding. (Appendix F) is statistically supported. The results of the t-test suggest that the means of the two groups are different (M_{group2} = 18.48, M_{group1} = 38.95; t (193.868) = -7.395, p < 0.001). The results of the ANOVA also indicate that the means of the two groups are different ($M_{group2} = 18.48$, $M_{group1} = 38.95$; $F(1,198) = 54.686$, $p < 0.001$). Therefore, the contention that compatibility would have a stronger positive effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externality receives strong support (i.e., H_{2a}).

Next, the model explores social process dimensions that provide the most significant contribution to recognize the importance of ease of use on adoption. H_{2b} predicts that complexity has a stronger negative effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externalities, which produces a decelerated S-shaped diffusion curve. In general innovations that are simpler to understand are adopted more rapidly than innovations that require individuals to develop new skills and understandings (Rogers 1995). Figure 12a and 12b clearly correspond with this conventional wisdom. Low levels of complexity yield S-shaped diffusion curves that the slope of the curve is steep and diffusion starts at relatively early stages of the diffusion process. On the other hand, high levels of complexity associated with innovations produce diffusion curves that lean toward the horizontal axis, indicating that diffusion occurs rather slowly. In the early stages of the diffusion process, the diffusion curves obtained by both low and high levels of complexity are broken apart after period 10, an implication that complexity is not a decisive factor for innovators.

Figure 12a: Effect of Complexity on Adoption Decisions When Personal Interaction and Network Externality Are Low While Social Pressure and Media Exposure Are High

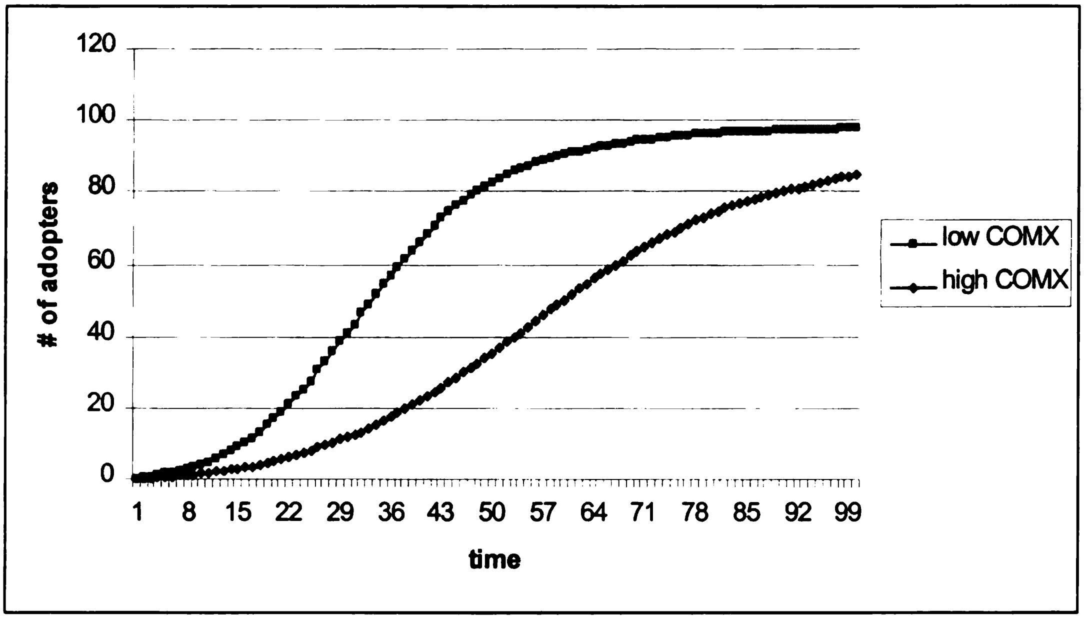
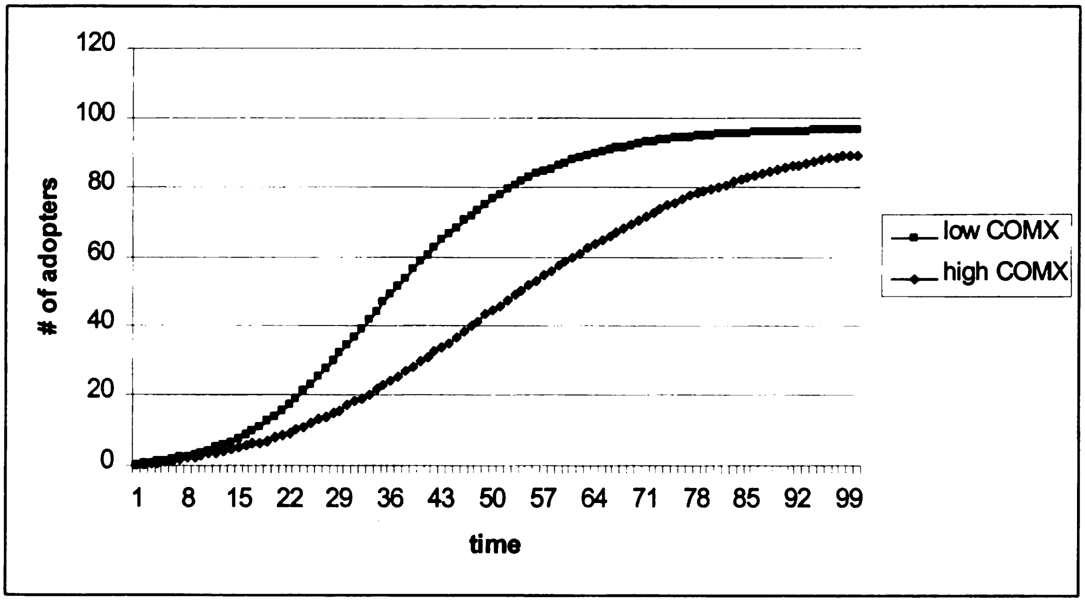


Figure 12b: Effect of Complexity on Adoption Decisions When Personal Interaction and Network Externality Are High While Social Pressure and Media Exposure Are Low



To test the H_{2b}, which predicts that trialability has a stronger positive effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externalities, the model is programmed with varying values of social process dimensions as before. Figure 12a and 12b indicate the contrasting results for two cases: personal interaction and network externality are low while social pressure and media exposure are high, and vice versa. The figures show that the relative importance of social pressure and media exposure is higher for recognizing the value of complexity characteristic of innovations on adoption decisions than that of personal interaction and network externality since the gap between the two diffusion curves (originating from both low and high levels of complexity) is greater in Figure 12a than 12b. This finding is also statistically supported by the results of ANOVA as well as t-test for independent samples (Appendix G). The results of the t-test show that the means of the two groups are different ($M_{group2} = 25.19$, $M_{group1} = 16.59$; $t(179.834) = 4.645$, $p < 0.001$). In the same way, the results of the ANOVA also indicate that the means of the two groups are different ($M_{group2} = 25.19$, $M_{group1} = 16.59$; $F(1,198) = 21.580$, $p < 0.001$). Therefore, H_{2b} is supported.

An examination of trialability's impact on adoption demonstrates the positive effect as theorized. Figures 14a and 14b suggest that if innovations can be tried, it is adopted more quickly than innovations that are not trialable, although the separation between these two points is not significant. In the early periods of diffusion, differences between low levels and high levels of trialability are minimal. When the innovation diffusion reaches period 25, high levels of trialability perform slightly

better than low levels of trialability in both figures. The two curves converge at the later stages of the diffusion process. Early and late convergence indicates that trialability is less important for innovators and early adopters as well as laggards. This finding contradicts with Rogers's (1995) assertion that trialability is particularly important for early adopters and innovators. In addition, in both cases (when personal interaction and network externality are low while social pressure and media exposure are high or vice versa), no clear take off point is observed, suggesting that diffusion occurs gradually over time. The results confirm Tornatzky and Klein's (1982) argument that trialability is not contributing to overall adoption decisions as strongly as relative advantage, compatibility, and complexity because the S-shaped curve leans more toward the right side. Finally, the figures show that the distance between high and low level trialability is pretty much the same in both figures, recommending that no clear differences exist among the four different social processes for realizing the trialability's value. In order to statistically confirm that the distance is not significant, t-test for independent samples and ANOVA are conducted (Appendix H). The results of the t-test show that the means of the two groups are not different (M_{group2} = 4.42, M_{group1} = 4.55; t (197.938) = -.302, p > 0.001). Similarly, the results of the ANOVA show that the means of the two groups are not different (M_{group2} = 4.42, M_{group1} = 4.55; F (1,198) = .091, p > 0.001). Therefore, H_{2c} is not supported.

Figure 13a: Effect of Trialability on Adoption Decisions When Personal Interaction and Network Externality Are Low While Social Pressure and Media Exposure Are High

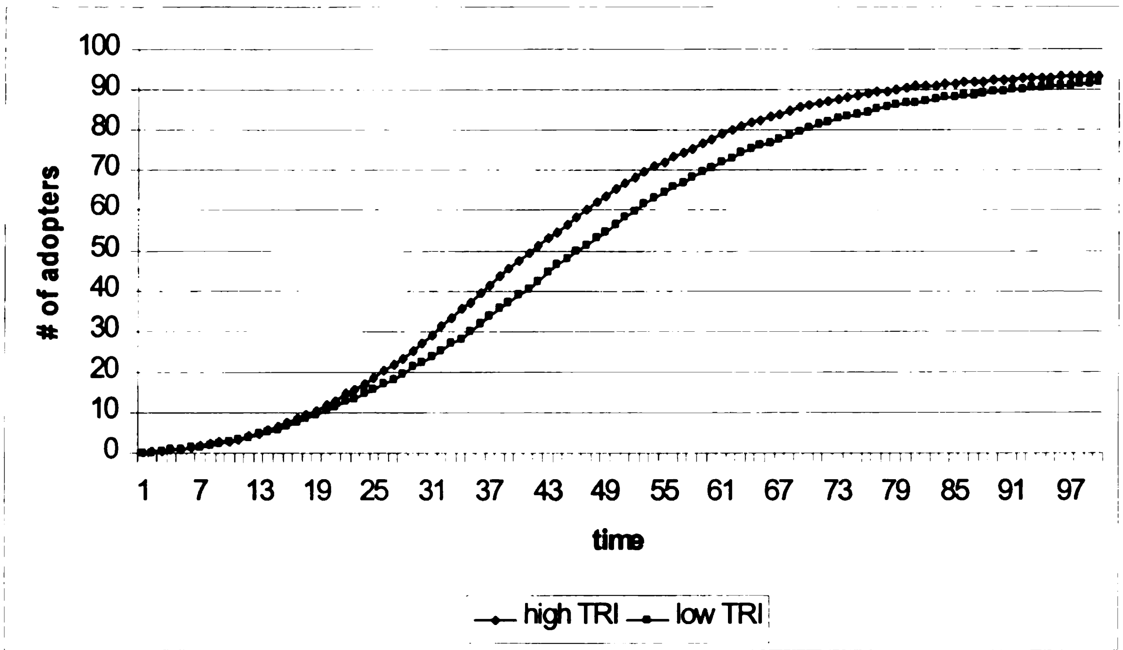
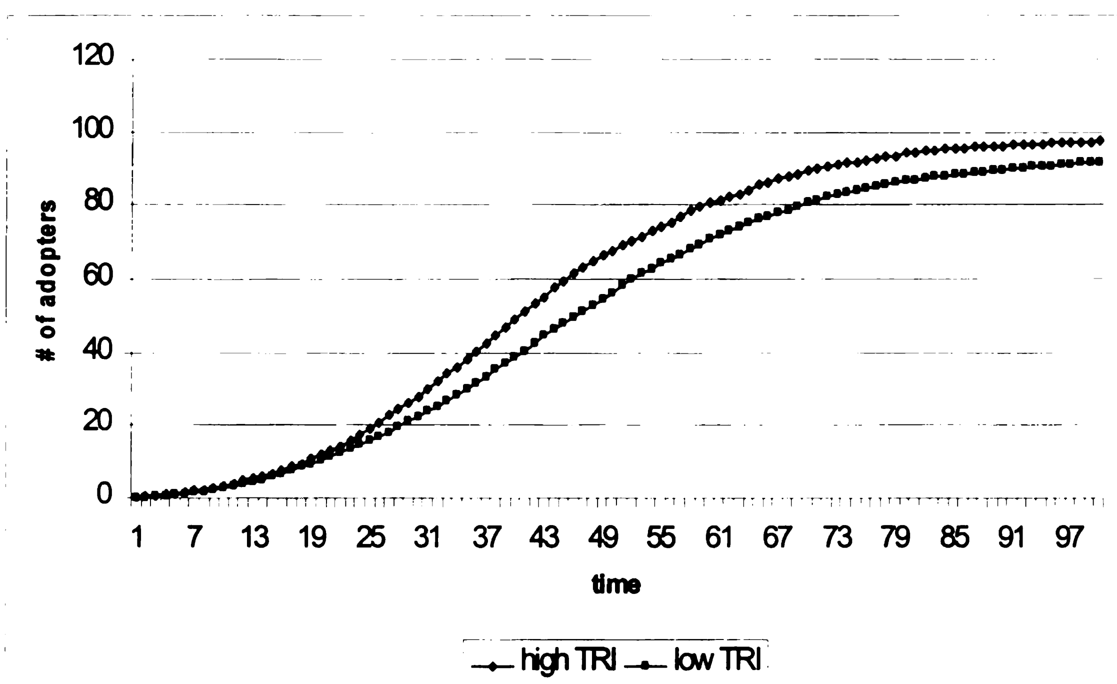


Figure 13b: Effect of Trialability on Adoption Decisions When Personal Interaction and Network Externality Are High While Social Pressure and Media Exposure Are Low



2.2.2. Effects of Individual Characteristics on Adoption

According to Rogers (2003), high status individuals are linked to a relatively large number of individuals and their characteristics cause others to imitate their behavior. High status individuals are more innovative, have greater product knowledge (Venkatraman 1989) and maintain a central position in the social system (Rogers 2003). Building on this knowledge, H_{3a} predicts that social status has a stronger positive effect on aggregate adoption when personal interaction and network externalities are more pronounced than media exposure and social pressure. The findings presented in Figure 14a and 14b support this body of research that the status of individuals in a social system plays a significant role in adoption decisions. Figure 14a shows that the adoption and diffusion rate is much higher when the status of an individual is high as oppose to when the status is low. Figure 14b confirms this finding, (i.e., there is a considerable difference between the "high status curve" and the "low status curve"). Higher levels of status produce a diffusion curve that is superior (i.e., the slope of the curve is steeper and product take off point is sooner) to those produced with lower levels of status.

Figure 14a: Effect of Social Status on Adoption Decisions When Personal Interaction and Network Externality Are High While Social Pressure and Media Exposure Are Low

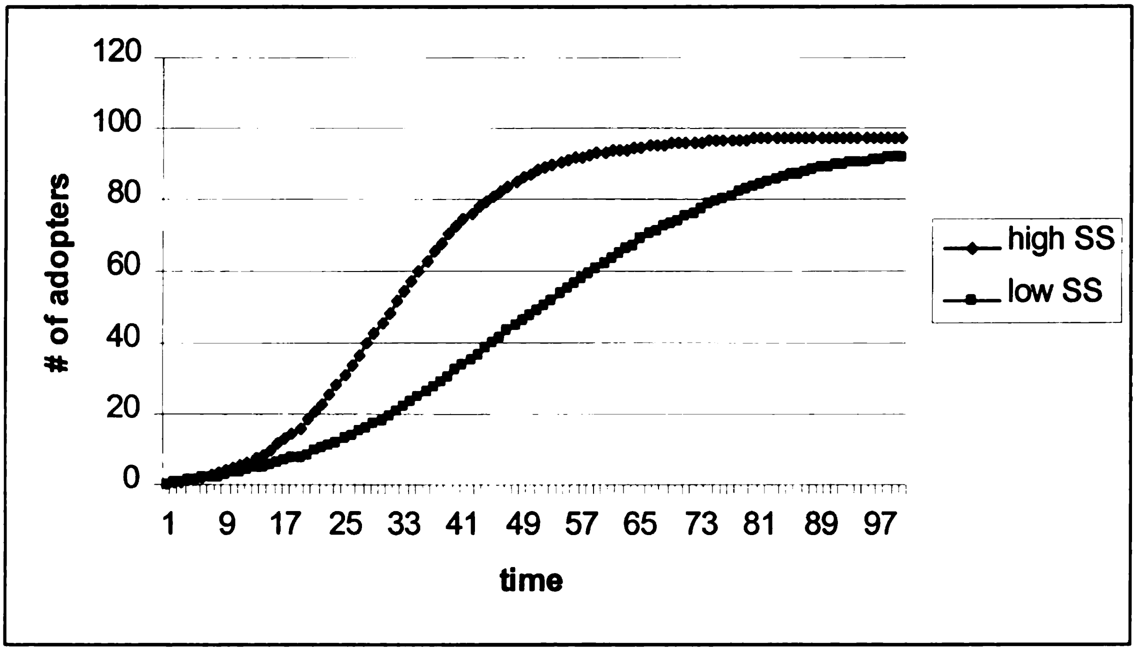
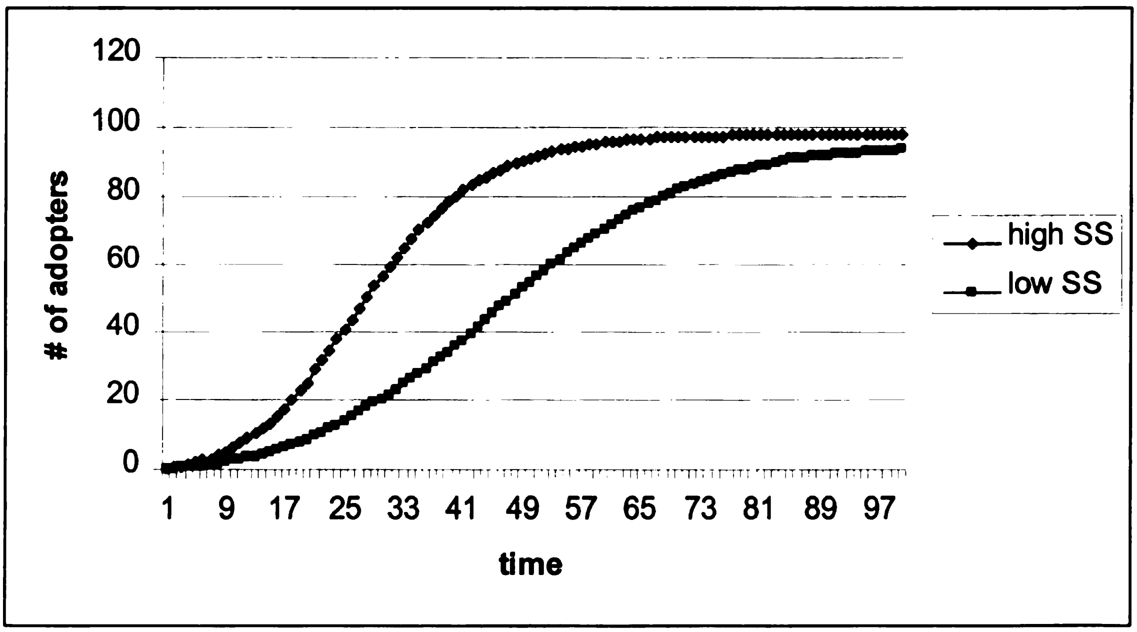


Figure 14b: Effect of Social Status on Adoption Decisions When Personal Interaction and Network Externality Are Low While Social Pressure and Media Exposure Are High



However, no noteworthy differences are found among social process dimensions. It seems the take off point is slightly earlier for the high status diffusion curve in Figure 14b when compared to Figure 14a. This difference can be attributed to the high value of media exposure as high status individuals tend to expose extensively to all forms of external communication. Both figures convincingly illustrate that the differences for diffusion rates between high and low status are minimal. In addition, t-test and ANOVA are conducted to ensure that differences are not significantly significant (Appendix I). The results of t-test indicate that the means of the two groups are not significantly different ($M_{group1} = 19.59$, $M_{group2} = 19.66$; $t (197.459) = -.032$, $p > 0.001$). Likewise, the results of the ANOVA show that the means of the two groups are not different ($M_{group1} = 19.59$, $M_{group2} = 19.66$; $F (1,198) = .001$, $p > 0.001$). This finding implies that the social process dimensions do not play a significantly different role for increasing the role of social status on adoption decisions. This suggests that H_{3a} is not supported.

The model also explores the role of perceived risk associated with innovations on adoption. H_{3b} formally states that perceived risk has a stronger negative effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externalities, which eventually will result in a decelerated S-shaped diffusion curve. To the extent that a potential adopter cannot always be certain about all of the advantages of an innovation, risk is perceived to be a factor in most adoption decisions. This notion is clearly captured in Figure 15a and 15b. At a low level of perceived risk, diffusion progresses rapidly and the slope of the S-shaped curve is steep. At a high level of perceived risk, diffusion occurs at a much slower rate, and the slope of the curve inclines more toward to horizontal axis. Personal interaction has a very significant, positive effect on reducing uncertainty associated with an innovation. As a direct result of this, risk declines and both adoption rate and eventually the diffusion rate increases.

Figure 15a: Effect of Perceived Risk on Adoption Decisions When Personal Interaction and Network Externality Are High While Social Pressure and Media Exposure Are Low

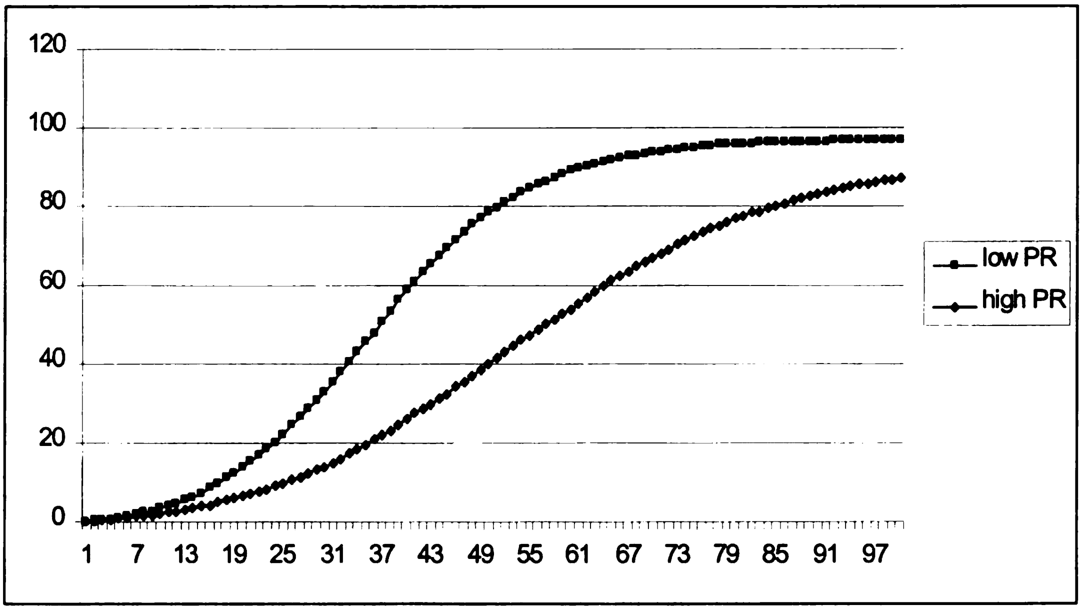
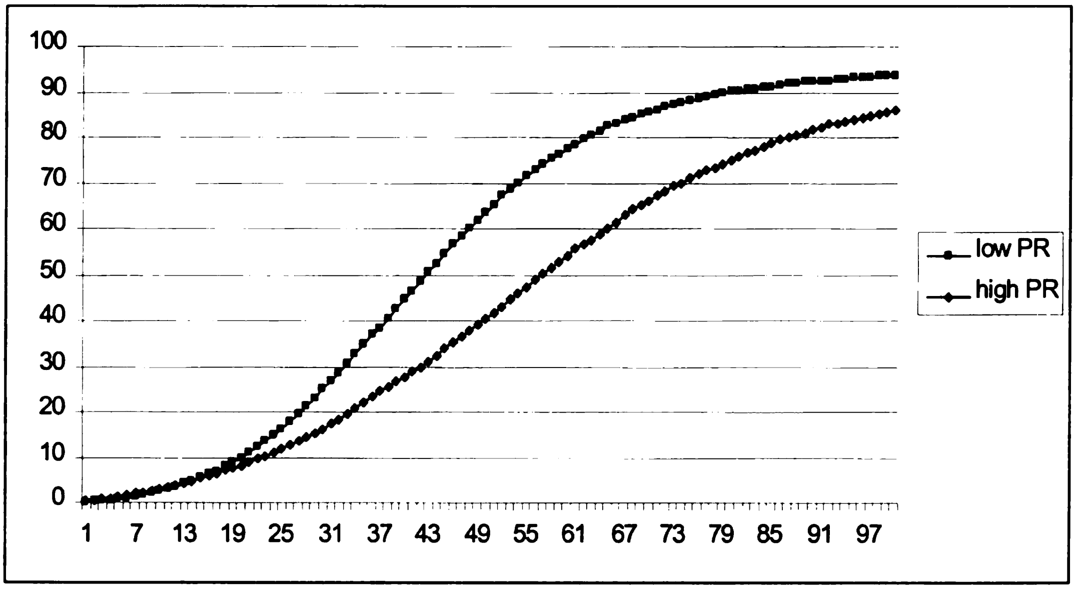


Figure 15b: Effect of Perceived Risk on Adoption Decisions When Personal Interaction and Network Externality Are Low While Social Pressure and Media Exposure Are High



As shown in both figures, the distance between low and high risk curves increases as the level of personal interaction and network externality gets higher. Analysis of t-test and ANOVA (Appendix J) also indicate statistical differences in figures. The results of t-test indicate that the means of the two groups are significantly different ($M_{group1} = 19.86$, $M_{group2} = 12.26$; $t\ (172.542) = 5.025$, $p < 0.001$). Likewise, the results of the ANOVA show that the means of the two groups are different ($M_{group1} = 19.86$, $M_{group2} = 12.26$; $F\ (1,198) = 25.255$, $p < 0.001$). Therefore, this finding supports H_{3b}. In addition, both figures exhibit that risk is not a major factor for innovators in their adoption decisions. In addition, even with low levels of perceived risk, some late adopters and laggards still do not adopt. The possible explanation to this can be the importance of other factors. For some late adopters and laggards, a low level of risk by itself is not an absolute driver for their adoption decision. Low risk should be combined with others attributes, such as greater benefits and less complexity.

3. The Second Study – International Adoption Behavior

Although the first model clearly shows the relative importance of the different dimensions of social processes as drivers of adoption and provides insights in terms of how innovation and individualistic characteristics play a role on adoption decisions, these findings may not be applicable to all countries. Previous research suggests that different cultural norms produce systematic differences in consumer adoption behavior of new products (Steenkamp et al. 1999; Stremersch and Tellis 2004; Van den Bulte and Stremersch 2004; Yeniyurt and Townsend 2003). Therefore, the second model is conducted, which investigates four components of culture (i.e., power distance, individualism, masculinity, and uncertainty avoidance) that have been found to be important determinants of international new product adoption and explores how each of social processes dimensions react to these cultural components.

3.1. Method

The second cellular automata model is formed by using the similar logic as the first model. The model excludes the innovation characteristics from the formula and includes four additional cultural parameters. The probability of an individual to adopt an innovation at time t is computed the same way:

$$\text{AdoptionProb}_{(t)} = [1 - (1\text{-p})\ (1\text{-q})^{k(t)}]$$

where *k(t)* is the number of previous adopters at time *t*.

Because of the exclusions of innovation characteristics and inclusions of cultural dimensions, the computation for *p* and *q* slightly differ from the first study and are computed as follow:

$$p = e^{\beta_0} \cdot IDV^{\beta_{IDV}} \cdot e^{\beta_{ME}} \cdot e^{\beta_{SP}} \tag{4}$$

where

IDV = individualism factor score.

β_{IDV} = the adoption probability that an individual will be affected by individualistic culture.

and

$$q = e^{\beta_0} \cdot PD^{\beta_{PDI}} \cdot MAS^{\beta_{MAS}} \cdot UA^{\beta_{UAI}} \cdot PR^{\beta_{PR}} \cdot SS^{\beta_{SS}} \cdot e^{\beta_{PI}} \cdot e^{\beta_{NE}} \tag{5}$$

where

PDI = power distance factor score.

MAS = masculinity factor score.

UAI = uncertainty avoidance factor score.

β_{PDI} = the adoption probability that an individual will be affected by power distance culture.

β_{MAS} = the adoption probability that an individual will be affected by masculinity culture.

β_{UAI} = the adoption probability that an individual will be affected by uncertainty avoidance culture.

For each of the cultural factor scores, the study uses either the average or maximum Hofstede's scores[12]. The maximum score is used when working with any one of the cultural dimensions at hand while the others use the average scores for that run. For example, if the study is testing the effect of power distance, then power distance gets the maximum value of Hofstede's scores (i.e., 104). All other dimensions (individualism, masculinity, and uncertainty avoidance) get the average value of Hofstede's scores (43.16, 50.52, and 66.30 respectively). The minimum, maximum, and average values of Hofstede's scores are as follows:

	Minimum Score	Maximum Score	Average Score
Power Distance	11	104	59.58
Individualism	6	91	43.16
Masculinity	5	110	50.52
Uncertainty Avoidance	8	112	66.30

The model also uses the coefficients associated with each of the cultural dimensions from the previous studies as its inputs (Stremersch and Tellis 2004; Van den Bulte and Stremersch 2004; Yaveroglu and Donthu 2002; Yeniyurt and Townsend 2003). In this way, the model is grounded with past empirical results, which allow us to get closer to reality as much as possible. Coefficient ranges for each of the cultural dimensions are set as follow:

Power Distance	-0.081 ; -0.323
Individualism	0.101 ; 0.411
Masculinity	0.062 ; 0.277
Uncertainty Avoidance	-0.023 ; -0.137

[12] Complete listing of countries used in the study is provided in Appendix C.

Like the first model, the programming part of the model is done in the C# (i.e., C Sharpe) language. Again, in each run, the population consists of 100 potential adopters and this population is divided into five adopter categories with respected percentages (see Appendix B). All members of the population are in a "*potential adopter*" state initially. For each period, the status change of each consumer is assessed on the basis of the probability described above (Equations (1), (4), and (5)).

3.2. Simulation Results

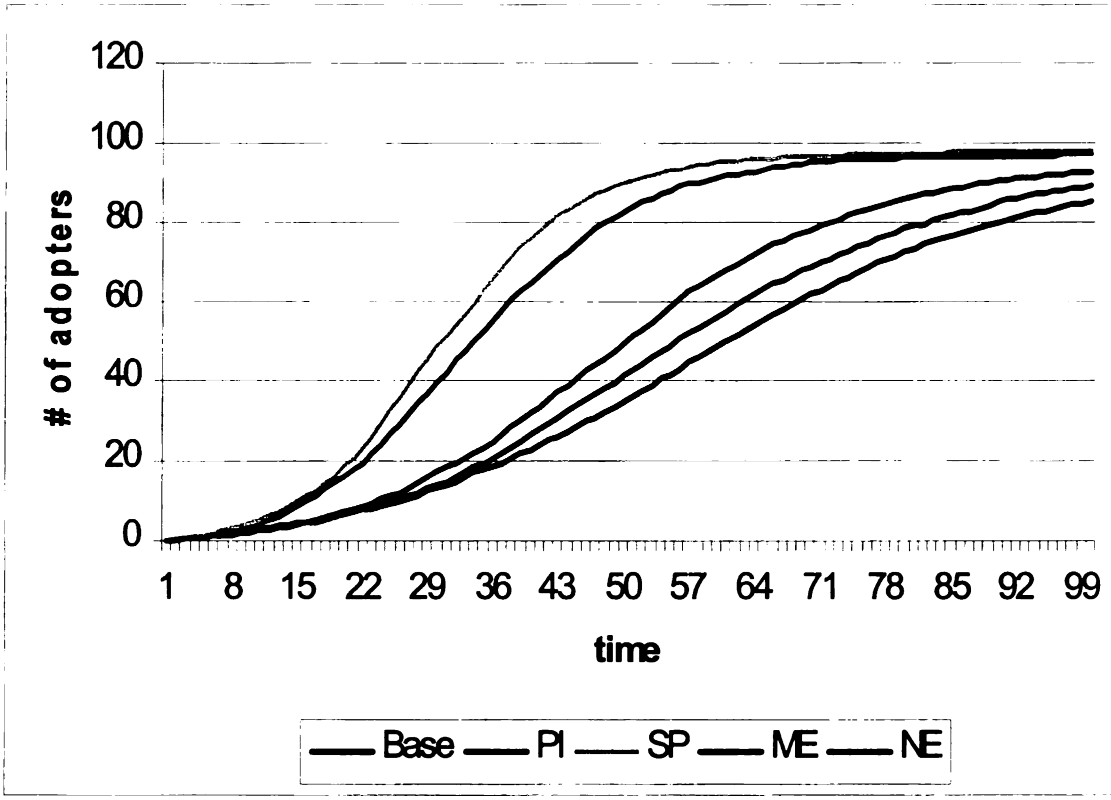
The second model explores the universality of the first model by incorporating Hofstede's cultural dimensions. Examination of personal interaction, social pressure, media exposure, and network externality's effect on adoption in different cultural environments yields interesting results.

3.2.1. Effects of Social Process Dimensions on Adoption in Power Distance Cultures

H_4 predicts that in high-power distance cultures, personal interaction and network externalities' effects will be more pronounced than those of media exposure and social pressure on adoption decisions when compared to low-power distance cultures. Figure 16 shows that as social pressure and personal interaction increase, adoption, and subsequently diffusion, happen quickly. The slope of the S-shaped diffusion curve is steep, and sales take off occur relatively early in stages of the diffusion process. Because in cultures with a high degree of power distance, status and age are important factors, individuals tend to emulate the adoption behavior of their superior. Thus, although the study is predicted to get a less significant effect from social pressure, it is not a total surprise to see the importance of social pressure on adoption in high-power distance cultures.

The importance of personal interactions on adoption is also observed as expected since individuals in power distance cultures tend to be less innovative, giving higher weight to product related information coming from their peers, other than media. Because of the same reason, the effect of media exposure on adoption is found to be minimal. In the case of network externality, the study theorized a positive strong relationship between network externality and adoption. The rational is in high-power distance cultures, individuals adopt the product for symbolic reasons and care less about whether the product will survive in the long run. However, the results indicate that the effect of network externality on adoption decisions does not quite reach the theorized relationship. One meaningful explanation for the lack of this result may be the fact that network externalities create uncertainty faced by potential adopters, as uncertainty causes potential adopters to delay their purchasing decisions. In sum, the argument that personal interaction and network externalities' effects will be more prominent than those of media exposure and social pressure on adoption decisions in high-powered distance cultures (i.e., H_4) is partially supported since results provide support for personal interaction and media exposure arguments, but not for social pressure and network externality.

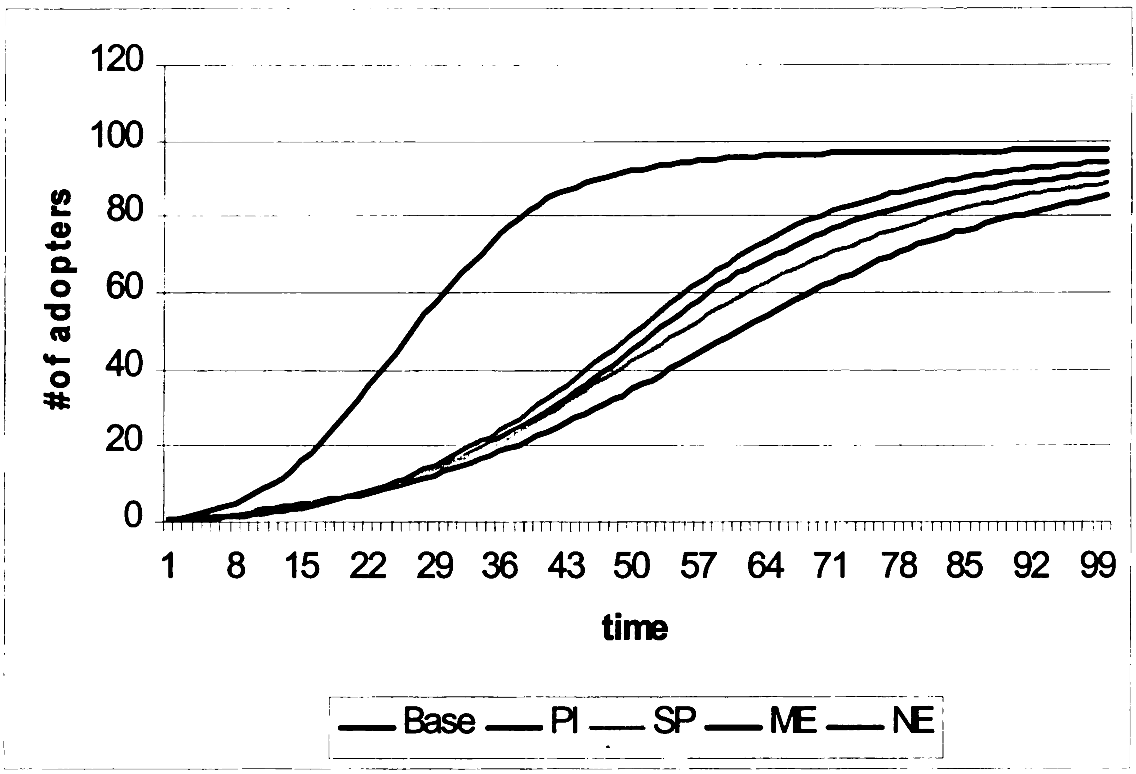
Figure 16: Effects of Personal Interaction, Social Pressure, Media Exposure, and Network Externality on Adoption Decisions in Power Distance Cultures



3.2.2. Effects of Social Process Dimensions on Adoption in Individualistic Cultures

H_5 expects that in individualistic cultures, media exposure and social pressure' effects will be more pronounced than those of personal interaction and network externalities on adoption decisions when compared to collectivistic cultures. A comparison of social process dimensions on adoption decisions in individualistic cultures yields some interesting results. It is evident from Figure 17 that the effect of media exposure on adoption is more pronounced than any of the other three social process dimensions' effects. As people in individualistic cultures value novelty and variety more, they tend to use media more, thus, this finding is not surprising. Similar logic explains why the effect of personal interaction is minimal in these cultures.

Figure 17: Effects of Personal Interaction, Social Pressure, Media Exposure, and Network Externality on Adoption Decisions in Individualistic Cultures

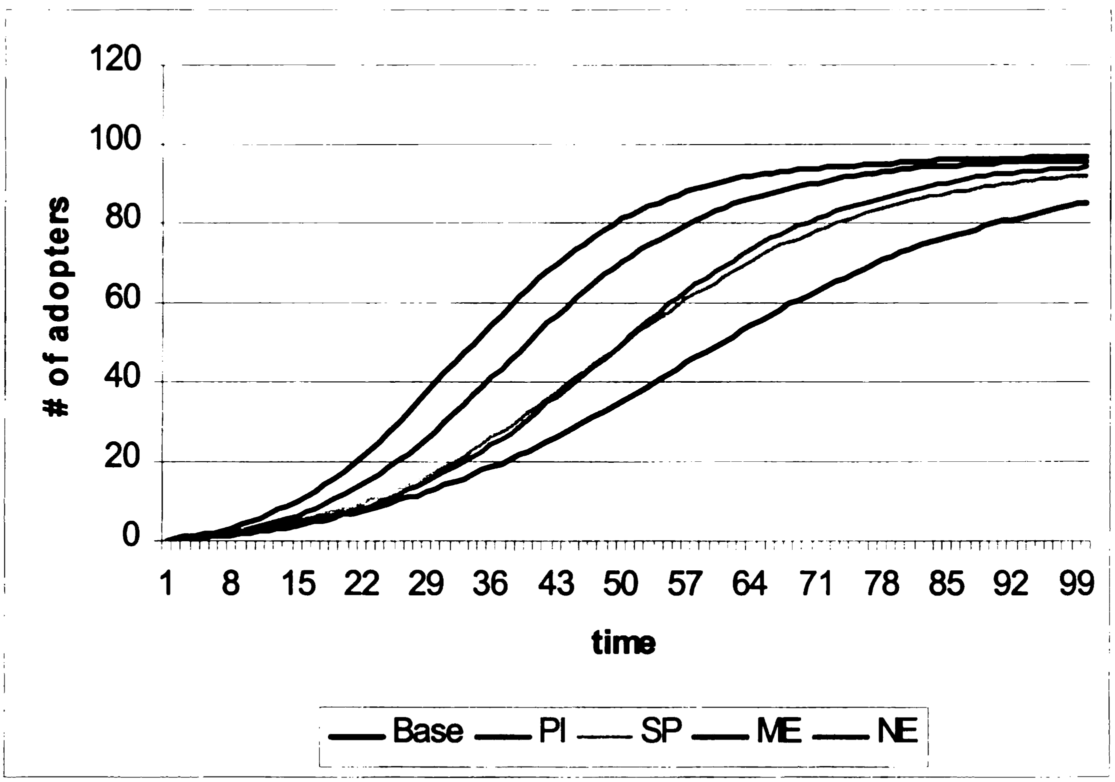


The diffusion curves obtained by network externality, personal interaction, and social pressure look fairly horizontal, indicating slower adoption process for all three dimensions. Figure 17 indicates that no clear sales take off point exists for each of these dimensions. In addition, the effects of these three dimensions on adoption are no different from the base case. The separation only starts after period 30. Among these three social processes, network externality performs slightly better (i.e., adoption, and subsequently diffusion occur quickly) than the other two dimensions. The slower rate of diffusion can be attributed to the fact that network externalities and competing technologies are strong discouraging factors to potential adopters since they create fear of not being the winning technology. Finally, a negligible role of social pressure on adoption is expected since in these cultures, individuals' overall well being supersedes the needs of the group, therefore, individuals do not feel much pressure. These results support the role of media exposure, personal interaction, and network externality on adoption in individualistic cultures as hypothesized, but not for social pressure. Therefore, these results indicate that H_5 is partially supported.

3.2.3. Effects of Social Process Dimensions on Adoption in Masculine Cultures

Figure 18 illustrates the effects of all social process dimensions on adoption. Contrary to what was predicted, (which states that in masculine cultures, personal interaction and network externalities' effects will be more pronounced than those of media exposure and social pressure on adoption decisions when compared to feminine cultures) the steepest diffusion curve is obtained by media exposure. This finding can be attributed to the specific characteristic of masculine culture. In these cultures, self achievement and success are important factors. Therefore, individuals may adopt new products faster as these products allow them to show off their achievements. As a result, individuals may tend to use media more extensively than interpersonal interaction to gather useful information about a new product's risks and benefits.

Figure 18: Effects of Personal Interaction, Social Pressure, Media Exposure, and Network Externality on Adoption Decisions in Masculine Cultures



The effects of social pressure and network externality on adoption produce almost identical results. As shown in Figure 18, diffusion curves obtained through cultural-baseline model[13], social pressure, and network externality all appeared to have a similar trajectory until period 25, an indication that social pressure and network externality do not have a major influence on individuals who belong to the

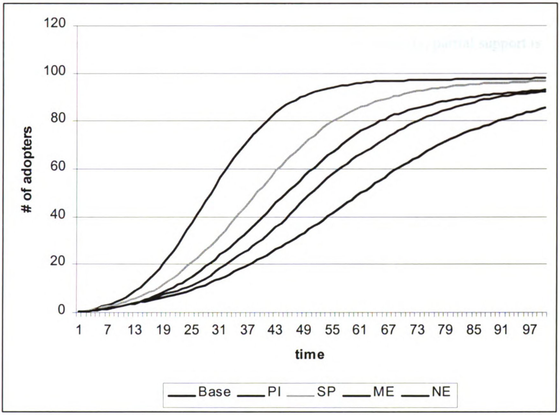
[13] In the cultural-baseline model, the values for all cultural dimensions are low (i.e., $\beta_{PDI} = 0.1$, $\beta_{IDV} = 0.1$, $\beta_{MAS} = 0.1$, and $\beta_{UAI} = 0.1$)

innovator adopter category in these cultures. Although social pressure and network externality's effects on adoption does not seem substantial, it is evident from the figure that these two factors still play a modest role in adoption decisions, as the distance from their diffusion curves to cultural-baseline model diffusion curve is significant. Consequently, the results partially support H_6.

3.2.4. Effects of Social Process Dimensions on Adoption in Uncertainty Avoidance Cultures

H_7 predicts that in high-uncertainty avoidance cultures, personal interaction and network externalities' effects will be more pronounced than those of media exposure and social pressure on adoption decisions when compared to low-uncertainty cultures. Because individuals in uncertainty avoidance cultures are generally not willing to take risks, they are hesitant to adopt a new product as soon as it is introduced to the marketplace. By interacting with the other members of their society, individuals try to collect product related information and reduce the potential risk associated with the innovation. Therefore, it is reasonable to assume that the effects of personal interactions on adoption will be greater than that of media in uncertainty avoidance cultures. Figure 19 confirms this contention.

Figure 19: Effects of Personal Interaction, Social Pressure, Media Exposure, and Network Externality on Adoption Decisions in Uncertainty Avoidance Cultures



As shown in Figure 19, the effect of network externality on adoption is minimal. This can be attributable to one important characteristic of network externality, in that it carries a risk of not being the dominant technology in the long run, which was the case for Sony's Betamax videocassette tape recording format. Batemax was the most popular video format until 1985. However, the market turned sharply towards VHS in the mid-eighties. Finally, although social pressure provides some effect on adoption, this effect is less than what was predicted in Hypothesis 7. This may be an indication of how important it is to reduce uncertainty and risk associated with new products in these cultures. If there is even a small amount of uncertainty and risk with the product, regardless of pressure coming from the social system, individuals will be reluctant to adopt. Although results provide strong support for media exposure's role on adoption in uncertainty avoidance cultures as hypothesized, because of the weak support for network externality, partial support is provided for H_7.

CHAPTER 5

DISCUSSION

The goal of this study was to advance the innovation diffusion literature by untangling the complex relationships among product innovation characteristics, individual characteristics, social process dimensions, and innovation adoption. The study contended that differences in diffusion patterns are in fact the result of individual level variations in adoption decisions. If the drivers of the adoption processes can be understood, a more comprehensive understanding of innovation diffusion may be provided. Therefore, the two models (domestic and international) presented in this study can be considered as a valuable conceptualization of innovation adoption and therefore, innovation diffusion.

The results show that the relative importance of the different social process dimensions as drivers of product adoption varies for both product innovation and individualistic characteristics. In terms of product innovation characteristics, personal interactions and network externalities are more essential social process dimensions than social pressure and media exposure for recognizing the value of the relative advantage attributes of product innovation on adoption decisions. The supported impact of personal interactions on dissemination of innovations provides more evidence for Goldenberg et al.'s (2001b) argument that beyond a relatively early stages of diffusion process, the efficacy of media exposure diminishes and personal interactions turn out to be the key forces driving diffusion. The finding suggests that potential adopters will acquire more information about the product and be better able to see the advantages of the product as the level of communications among individuals increases. This in turn reduces the uncertainty associated with the innovation and accelerates the adoption of the innovation.

The results of this study also demonstrate that compatibility and complexity will have a stronger effect on aggregate adoption when media exposure and social pressure are more pronounced than personal interaction and network externality. This finding is consistent with the theorized argument that potential adopters value marketing efforts (e.g., advertising) more than personal interactions in terms of gaining useful insights about the innovation since individuals have different levels of knowledge and skills as well as different compatibility tolerance levels with respect to a specific innovation and perceive different levels of complexity and compatibility in its use.

Importantly, the study also indicates that no significant differences exist among the four dimensions of social processes as per their role in recognizing the value of trialability and observability on adoption. A possible explanation for this result may be attributable to Tornatzky and Klein's (1982) finding that the relative importance of trialability and observability on adoption decisions are weaker than that of the relative advantage, compatibility, and complexity. Because of this low level of importance, the differences in effects coming from different social dimensions are negligible.

Although the study reveals that the status of individuals is an important determining factor for innovation adoption, the effects of personal interaction and network externality are not significantly different from the effects of media exposure and social pressure in recognizing the role of social status on adoption decisions. These results seem counterintuitive in that personal interaction should play an essential role in particular for low status individuals (i.e., late adopters) since low status individuals tend to reduce uncertainty associated with the innovation by collecting product related information from high status individuals (i.e., early adopters). No meaningful difference between effects can be attributed to the importance of media exposure for high status individuals. High status individuals tend to be more innovative, value novelty more, and use the media more extensively than personal interaction to gather information about the innovation (Rogers 2003). It seems that the importance of personal interaction for low status individuals is offset by the importance of media exposure for high status individuals, which results in non-significant differences in the overall effect.

In the case of perceived risk, the study suggests several interesting findings. First, risk is not found to be a key factor for innovators in their adoption decisions. Secondly, for some late adopters and, especially for laggards, the low level of risk associated with an innovation alone is not an absolute driver for their adoption decision. Therefore, low level of risk should be combined with some other attributes of a product, such as greater benefits and less complexity. Finally, personal interaction appears to be the most potent driver of reducing uncertainty associated with an innovation. By interacting with people who have already adopted the innovation, potential adopters learn more about the innovation and get familiar with its potential risks. This in turn reduces uncertainty and facilitates adoptive behavior. This result adds to findings that learning product related information through interacting with adopters eliminates uncertainty of outcomes, which in turn lowers the risk of adoption (e.g., Valente 1995)

The results advance the international marketing literature as well. The results show that in power distance cultures, the relative importance of social pressure and personal interactions are more pronounced than the relative importance of media exposure and network externalities. This finding implies that individuals in high-power distance cultures tend to emulate the adoption behavior of their superior. In the case of individualistic cultures, because people value novelty and variety more, media appears to be the most potent driver of innovation adoption. The effects of the other three social process dimensions on adoption are minimal. In the case of masculine cultures, media again emerges as the most powerful driver of innovation adoption followed by social pressure and network externality. The relative importance of media exposure on adoption makes sense in these cultures as individuals tend to adopt new products at the early stages of product life cycle, hoping that these newly adopted products allow them to show off their achievements. Finally, in the case of high-uncertainty avoidance cultures, personal interaction is the most effective driver of innovation adoption because they try to reduce the potential risk associated with the new product by interacting with other members of their society.

Theoretical Contributions

This study contributes to the theory of innovation diffusion in several ways. First, the study bridges micro-level adoption studies and macro-level diffusion studies by incorporating, what is believed to be missing boundary parameters, that is social process dimensions. Diffusion of innovation theory argues that media as well as interpersonal contacts provide information about an innovation and influence opinions of potential adopters on adoption. However, the challenge is how interpersonal and external effects turn adoption into diffusion. By addressing the link between micro-level adoption and macro-level diffusion, this study meets this challenge and provides a new foundation for the literature; that is, aggregated adoption behavior (i.e., diffusion) emerges from heterogeneous and complex interactions among individuals. The models presented in this study offer both a macro and a micro level representation, which provides a richer portrayal of the overall dynamics of diffusion.

Second, the study examines the joint effects of innovation and individual characteristics on adoption decisions under the different levels of the social process dimensions. Although Rogers (1995) theorized that innovations perceived as having greater relative advantage, compatibility, trialability, observability, and less complexity would be adopted more quickly than other innovations, there has been no empirical evidence linking these innovation characteristics with individuals' own characteristics. Because innovation and individual characteristics correlate with each other (e.g., *innovators* are interested in new ideas and have an ability to understand and apply complex technological knowledge. Thus, higher complexity associated with an innovation is not considered to be a crucial determining factor on adoption for *innovators*, although it likely is for *laggards*), by exploring the joint effects, this study provides a more complete understanding of dynamics that are related to the adoption, and subsequently diffusion of innovations. In addition, the empirical evidence from this study contributes to the marketing literature by providing a new theoretical mechanism by which diffusion is linked to innovation and individual characteristics as well as social process dimensions.

Third, a key moderating role of network externalities is studied in this research. Prior research has provided very little insights with regard to network externalities' determinants. The effects of network externalities have typically been investigated as exogenous variables and their moderating role between innovation and individualistic characteristics and adoption decisions have gotten little attention in innovation diffusion literature. Because accurate estimation of the innovation diffusion involves a comprehensive understanding of the role of network effects, investigating this notion is especially important in advancing the literature.

Finally, the study also examines the relative importance of social process dimensions on adoption in different cultural contexts. By studying Hofstede's cultural dimensions, the generalizability or universality of the results across markets is established. Additionally, the results contribute to the international marketing literature by providing significant evidence regarding the moderation effects of culture on social process dimensions.

Managerial Implications

The model developed in this study provides top management an understanding of how variations in individuals' adoption decisions influence overall diffusion patterns. Managers must recognize that interpersonal communication is a very important tool for communicating the characteristics of innovations. Knowing that innovations carry a certain risk when they are first introduced to market, it is important to provide extensive information about the characteristics of the innovation, as individuals attempt to reduce this risk by acquiring information about the innovation. Since most innovation adoption processes tend to be very social in nature, the influence of word-of-mouth is considerably more important in reducing uncertainty and risk associated with the innovation. Therefore, managers should look for opportunities to create word-of-mouth for their product. For instance, firms may consider participating in online communities as a means to create demand for their products. Online communities provide opportunities to express and access others' opinions, and adjust one's own thoughts and actions in light of input from others. Firms may post positive messages regarding their own products or in certain situations, may provide referral rewards.

Modeling the diffusion of an innovation is a complex practice. The models presented in this research bridge the micro and macro perspectives, therefore providing advantages that other models lack. One obvious benefit would be the use of these models in forecasting. Accurate forecasts are critical in the "production, distribution, marketing, and general planning efforts of these products" (Parker 1994, p. 353). Macro models such as the Bass model have traditionally been used for these purposes. Given the number of factors that influence the adoption of a new product, these models are occasionally unsuccessful at providing precise forecasts, which can sometimes lead to disastrous consequences for a firm. The models introduced in this study, which follow the micro modeling approach but can still be aggregated to obtain a macro perspective, may therefore be superior in their forecasting ability.

New product introduction is one of the most multifaceted decisions that the managers of multinational companies cope with (Talukdar et al. 2002). Cultural dissimilarities add even more complexity and have an important influence on all aspects of marketing practices (Takada and Jain 1991). For global product managers, one big question is how fast a new product is likely to sell in different countries. Hence, a good understanding of cultural effects on the adoption of new products in a specific country will help management to forecast demand more accurately. Considering that the results of this study indicate a significant relationship between power distance, individualism, masculinity, uncertainty avoidance and the social process dimensions, managerial teams have additional parameters to add to their existing forecast equation. Countries that have similar scores in these dimensions are expected to have similar new product adoption rates. Additionally, firms should first target countries with higher individualism and masculinity, but lower power distance and uncertainty avoidance scores when they offer a new product. In this case, ceteris paribus, firms should target countries like Australia, Ireland, New Zealand, Switzerland, and United States, where people are open to new ideas and novelty for their international expansions.

The findings of significant differences across countries in adoption and diffusion pattern of innovations resonates with research that supports a localized approach (Szymanski, Bharadwaj, and Varadarajan 1993; Zou and Cavusgil 2002). It seems that because culture is an important factor in adoption of innovations, firms need to have different marketing approaches. For instance, in countries where the degree of openness is greater, firms should concentrate more on marketing efforts to inform consumers about the innovation. A concentration on generating word-of-mouth for innovations may be a more appropriate approach for countries where tolerance to uncertainty and risk is low.

Limitations and Future Research Directions

The results of the present study are subject to the limitations of the model. Since a simulated model is unable to imitate all aspects of an actual market, additional studies are needed to confirm these findings and develop more specific strategies. The effect of marketing efforts (e.g., advertising) is expressed only through parameter p, yet communication among individuals can be also affected by marketing efforts.

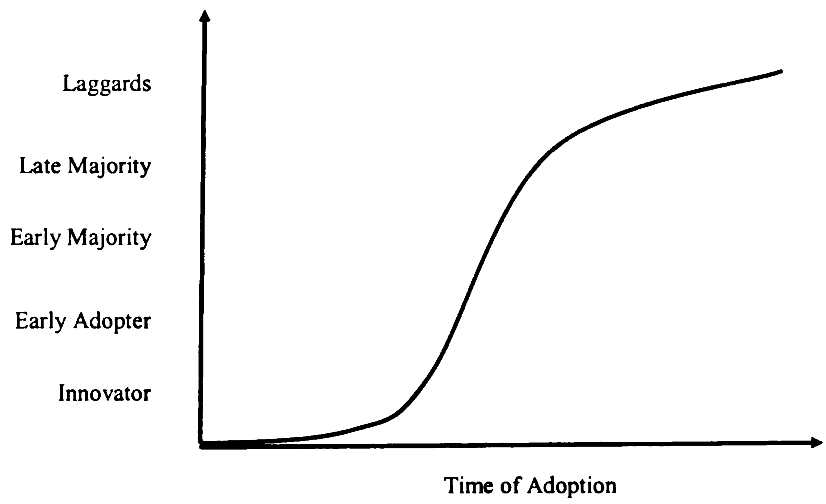
Many possible extensions of the model presented in this study would be interesting to pursue. One extension would be to examine the adoption of new technologies within organizations using a simulation model. Investigating what factors contribute to the adoption of new technology within firms and the role of personal interactions in this adoption process may lead to interesting findings. One obvious reason for such a need is that in order to be successful in today's competitive environment, firms should continually search for a strategic advantage by adopting new technologies that produce advantages over their competitors. However, effective adoption of new technologies is often a major concern for management. Therefore, managers should have a clear understanding of the drivers that lead to the adoption of new technologies. Without having such an understanding, firms cannot create an environment that fosters the adoption of new technologies. In addition, examination of the role of the same social process dimensions on adoption decisions for firms rather than individuals would be a viable extension of this study as well.

One other way to extend the current study would be constructing models bringing the macro and micro diffusion approaches together, but restricting differences between members of the population on a few salient dimensions. This essentially segments the population into groups of collective individuals. Individuals within a group are considered to be homogeneous, and will not differ in their adoption behavior. Differences exist between groups which lead to various adoption patterns. A potential practical application would be to use market research data about segments of the population to fit the parameters of the model. Such models may be able to provide improved forecasts for a firm. The other possible extension of the model would be running with different product categories. Examining multiple product categories should provide some interesting results. For example, comparing high tech products with consumer durables may yield different outcomes. The relative importance of each of the innovation characteristics as well as social process dimensions may be different for different product categories.

Further research should also look at the adoption of innovation differences emerging from industrialized and emerging countries. This increases the ability to generalize the insights to many markets.

APPENDICES

Appendix A – S-Curve Example



Source: Rogers (1995)

Appendix A shows the cumulative percentage of the potential market (i.e., total number of adopters) that has made an initial purchase of a new product. As you move up and to the right of the S-curve in Appendix A, i.e., as you look at the rate of adoption of a new product over time by first time purchasers, you initially have the innovators buying the product, then early adopters, and so on as you move up the S-curve, until you get to the point of market saturation, where the last set of first-time buyers are known as the laggards.

Appendix B - Rogers's Adopter Categories

Rogers (1995; 2003) has proposed the most widely used and accepted classification of adopters, based on the timing of adoption. According to Rogers (2003) the adopters of innovations can be classified into five categories: 1) innovators, 2) early adopters, 3) early majority, 4) late majority, and 5) laggards.

(1) *Innovators* (pioneers) have several common characteristics. They can be said to be venturesome. They are interested in new ideas and have an ability to understand and apply complex technological knowledge. They bring new innovations into the social systems (Rogers 2003).

(2) *Early adopters* have the greatest opinion leadership in most systems. They are part of the social system and serve as role models for many other members of the social system. Early adopters decrease the uncertainty about a new idea by a communication process (Rogers 2003).

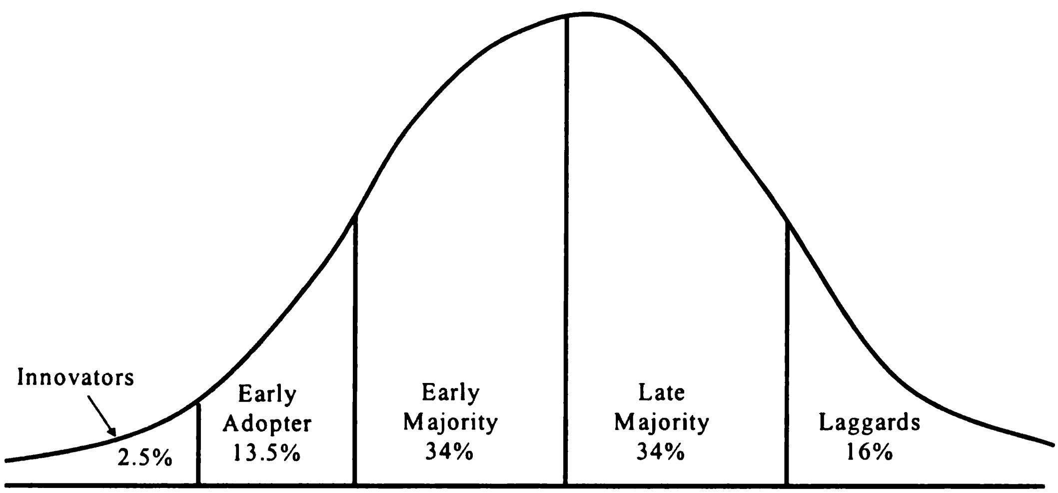
(3) *Early majority* wants some proof that the innovation is feasible before adopting it, but they still do not want to be the last ones. Their innovation decision takes relatively longer than that of former groups. (Rogers 2003).

(4) *Late majority* adopts new ideas just after the average member of a system. Adoption for them is both an economic necessity and increasing network pressure.

They also have relatively scarce resources, which mean that uncertainties related to the innovation must be considered carefully before the adoption. (Rogers 2003).

(5) *Laggards* are the last ones to adopt an innovation. Laggards make their decision according to past experiences. Laggards need to have a stable environment and they are not familiar with uncertainties. Their decisions are entirely rational and they are extremely traditional (Rogers 2003).

Rogers Adoption Curve



Appendix C – Countries Included in the Study and Their Hofstede Scores

	Power Distance	Individualism	Masculinity	Uncertainty Avoidance
Arab countries **	80	38	53	68
Argentina	49	46	56	86
Australia	36	90	61	51
Austria	11	55	79	70
Bangladesh *	80	20	55	60
Belgium	65	75	54	94
Brazil	69	38	49	76
Bulgaria *	70	30	40	85
Canada	39	80	52	48
Chile	63	23	28	86
China, Mainland	80	20	66	30
Colombia	67	13	64	80
Costa Rica	35	15	21	86
Czech Republic *	57	58	57	74
Denmark	18	74	16	23
East Africa **	64	27	41	52
Equator	78	8	63	67
Estonia *	40	60	30	60
Finland	33	63	26	59
France	68	71	43	86
Germany FR	35	67	66	65
Great Britain	35	89	66	35
Greece	60	35	57	112
Guatemala	95	6	37	101
Hong Kong	68	25	57	29
Hungary *	46	80	88	82
India	77	48	56	40
Indonesia	78	14	46	48
Iran	58	41	43	59
Ireland	28	70	68	35
Israel	13	54	47	81
Italy	50	76	70	75
Jamaica	45	39	68	13
Japan	54	46	95	92
Malaysia	104	26	50	36
Malta *	56	59	47	96
Mexico	81	30	69	82
Morocco *	70	46	53	68
Netherlands	38	80	14	53
New Zealand	22	79	58	49
Norway	31	69	8	50

Pakistan	55	14	50	70
Panama	95	11	44	86
Peru	64	16	42	87
Philippines	94	32	64	44
Poland	68	60	64	93
Portugal	63	27	31	104
Romania *	90	30	42	90
Russia *	93	39	36	95
Salvador	66	19	40	94
Singapore	74	20	48	8
Slovakia *	104	52	110	51
South Africa	49	65	63	49
South Korea	60	18	39	85
Spain	57	51	42	86
Surinam *	85	47	37	92
Sweden	31	71	5	29
Switzerland	34	68	70	58
Taiwan	58	17	45	69
Thailand	64	20	34	64
Trinidad *	47	16	58	55
Turkey	66	37	45	85
Uruguay	61	36	38	100
USA	40	91	62	46
Venezuela	81	12	73	76
Vietnam *	70	20	40	30
West Africa **	77	20	46	54
Max	**104**	**91**	**110**	**112**
Min	**11**	**6**	**5**	**8**
Ave	**59.58**	**43.16**	**50.52**	**66.30**

* Estimated values
** Regional estimated values
Arab countries = Egypt, Iraq, Kuwait, Lebanon, Libya, Saudi Arabia, United Arab Emirates
East Africa = Ethiopia, Kenya, Tanzania, Zambia
West Africa = Ghana, Nigeria, Sierra Leone

Appendix D – Analysis of the Distance between the Diffusion Curves Obtained When Relative Advantage is High Versus Low under the Varying Levels of Social Process Dimensions (H_{1a})

Table D-1: Test of Homogeneity of Variance

Levene Statistic	df1	df2	Significance
45.928	1	198	0.000

Table D-2: Descriptive Statistics

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Group 1	100	35.5370	20.73610	2.07361	31.4225	39.6515	.08	62.74
Group 2	100	24.9661	11.48349	1.14835	22.6875	27.2447	.74	41.10
Total	200	30.2516	17.53833	1.24015	27.8060	32.6971	.08	62.74

Table D-3: T-Test for Equality of Means Equal Variances Not Assumed

DF	t	Significance
154.503	4.460	0.000

Table D-4: Analysis of Variance (ANOVA)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5587.196	1	5587.196	19.888	.000
Within Groups	55623.800	198	280.928		
Total	61210.996	199			

Appendix E – Analysis of the Distance between the Diffusion Curves Obtained When Observability is High Versus Low under the Varying Levels of Social Process Dimensions (H_{1b})

Table E-1: Test of Homogeneity of Variance

Levene Statistic	df1	df2	Significance
8.277	1	198	0.004

Table E-2: Descriptive Statistics

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Group 1	100	7.9828	8.98362	.89836	6.2003	9.7653	.00	25.44
Group 2	100	6.4421	7.27733	.72773	4.9981	7.8861	.00	22.24
Total	200	7.2125	8.19104	.57919	6.0703	8.3546	.00	25.44

Table E-3: T-Test for Equality of Means Equal Variances Not Assumed

DF	t	Significance
189.821	1.333	0.184

Table E-4: Analysis of Variance (ANOVA)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	118.688	1	118.688	1.776	.184
Within Groups	13232.840	198	66.833		
Total	13351.528	199			

Appendix F – Analysis of the Distance between the Diffusion Curves Obtained When Compatibility is High Versus Low under the Varying Levels of Social Process Dimensions (H_{2a})

Table F-1: Test of Homogeneity of Variance

Levene Statistic	df1	df2	Significance
1.264	1	198	0.262

Table F-2: Descriptive Statistics

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Group 2	100	18.4757	18.09630	1.80963	14.8850	22.0664	-.05	51.74
Group 1	100	38.9548	20.96264	2.09626	34.7954	43.1142	.22	63.70
Total	200	28.7153	22.06587	1.56029	25.6384	31.7921	-.05	63.70

Table F-3: T-Test for Equality of Means Equal Variances Not Assumed

DF	t	Significance
193.868	-7.395	0.000

Table F-4: Analysis of Variance (ANOVA)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	20969.677	1	20969.677	54.686	.000
Within Groups	75923.938	198	383.454		
Total	96893.615	199			

Appendix G – Analysis of the Distance between the Diffusion Curves Obtained When Complexity is High Versus Low under the Varying Levels of Social Process Dimensions (H_{2b})

Table G-1: Test of Homogeneity of Variance

Levene Statistic	df1	df2	Significance
15.033	1	198	0.00

Table G-2: Descriptive Statistics

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Group 2	100	25.1907	15.03062	1.50306	22.2083	28.1731	.02	47.64
Group 1	100	16.5890	10.81420	1.08142	14.4432	18.7348	.08	32.48
Total	200	20.8899	13.75362	.97253	18.9721	22.8076	.02	47.64

Table G-3: T-Test for Equality of Means Equal Variances Not Assumed

DF	t	Significance
179.834	4.645	0.000

Table G-4: Analysis of Variance (ANOVA)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3699.462	1	3699.462	21.580	.000
Within Groups	33943.777	198	171.433		
Total	37643.239	199			

Appendix H – Analysis of the Distance between the Diffusion Curves Obtained When Trialability is High Versus Low under the Varying Levels of Social Process Dimensions (H_{2c})

Table H-1: Test of Homogeneity of Variance

Levene Statistic	df1	df2	Significance
0.108	1	198	0.743

Table H-2: Descriptive Statistics

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Group 1	100	4.4245	2.92602	.29260	3.8439	5.0051	.04	9.14
Group 2	100	4.5506	2.97817	.29782	3.9597	5.1415	.08	9.22
Total	200	4.4876	2.94546	.20828	4.0768	4.8983	.04	9.22

Table H-3: T-Test for Equality of Means Equal Variances Not Assumed

DF	t	Significance
197.938	-0.302	0.763

Table H-4: Analysis of Variance (ANOVA)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.795	1	.795	.091	.763
Within Groups	1725.680	198	8.716		
Total	1726.475	199			

Appendix I – Analysis of the Distance between the Diffusion Curves Obtained When Social Status is High Versus Low under the Varying Levels of Social Process Dimensions (H_{3a})

Table I-1: Test of Homogeneity of Variance

Levene Statistic	df1	df2	Significance
0.506	1	198	0.478

Table I-2: Descriptive Statistics

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Group 1	100	19.5912	13.73709	1.37371	16.8655	22.3169	-.08	40.96
Group 2	100	19.6560	14.47600	1.44760	16.7836	22.5284	.08	44.74
Total	200	19.6236	14.07592	.99532	17.6609	21.5863	-.08	44.74

Table I-3: T-Test for Equality of Means Equal Variances Not Assumed

DF	t	Significance
197.459	-0.032	0.974

Table I-4: Analysis of Variance (ANOVA)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.210	1	.210	.001	.974
Within Groups	39427.970	198	199.131		
Total	39428.180	199			

Appendix J – Analysis of the Distance between the Diffusion Curves Obtained When Perceived Risk is High Versus Low under the Varying Levels of Social Process Dimensions (H_{3b})

Table J-1: Test of Homogeneity of Variance

Levene Statistic	df1	df2	Significance
24.124	1	198	0.000

Table J-2: Descriptive Statistics

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Group 1	100	19.8572	12.58347	1.25835	17.3604	22.3540	.04	38.84
Group 2	100	12.2556	8.39389	.83939	10.5901	13.9211	-.68	24.16
Total	200	16.0564	11.32891	.80108	14.4767	17.6361	-.68	38.84

Table J-3: T-Test for Equality of Means Equal Variances Not Assumed

DF	t	Significance
172.542	5.025	0.000

Table J-4: Analysis of Variance (ANOVA)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2889.216	1	2889.216	25.255	.000
Within Groups	22651.296	198	114.400		
Total	25540.512	199			

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